Understanding Cash Flow Risk[*]

Sebastian Gryglewicz[†]   Loriano Mancini[‡]   Erwan Morellec[§]

Enrique Schroth[¶]   Philip Valta[‖]

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Abstract

Theory has recently shown that cash flow risk depends on the exposure of firms to short- and long-term cash flow shocks and the correlation between these shocks, with a higher correlation *reducing* risk. We provide granular estimates of these parameters for Compustat firms using a new filter that uses only cash flow data and the theoretical restrictions imposed by a canonical cash flow model. We show empirically that the estimated parameters have first-order effects on firms' policies, that firms with a higher estimated correlation between shocks implement riskier policies, and that the sign of this correlation determines that cash flow sensitivity of cash as predicted by theory.

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[†]Erasmus University Rotterdam. Email: gryglewicz@ese.eur.nl.
[‡]USI Lugano and Swiss Finance Institute. E-mail: loriano.mancini@usi.ch.
[§]EPF Lausanne, Swiss Finance Institute, and CEPR. E-mail: erwan.morellec@epfl.ch.
[¶]EDHEC Business School and CEPR. E-mail: enrique.schroth@edhec.edu.
[‖]University of Bern. E-mail: philip.valta@ifm.unibe.ch.

Starting with Gorbenko and Strebulaev (2010) and DeMarzo, Fishman, He, and Wang (2012), a growing theoretical literature in corporate finance argues that corporate policies should respond differently to permanent and transitory cash flow shocks. Indeed, permanent shocks affect not only a firm's immediate productivity and cash flows but also its future productivity and cash flows. By contrast, while transitory shocks affect immediate cash flows, they are uninformative about future expected profitability.[1] While the decomposition of shocks between transitory and permanent components has been used productively over the years in many areas of economics, it has received little attention in empirical corporate finance.[2] This is relatively surprising given that risk is considered a key driver of corporate policies and that theory has shown that cash flow risk generally depends on exposure to long- and short-term shocks and the correlation between these shocks.

The objective of this article is to start filling the existing void. We do so in four successive steps. First, we provide evidence that a majority of firms' operating cash flows are subject to permanent (non-stationary) shocks, thereby providing support for the cash flow model used in much of the dynamic corporate finance literature. Second, we develop a novel filter to decompose the cash flow shocks of publicly traded U.S. firms into permanent and transitory components and to estimate their primitive parameters. Third, we provide granular estimates of cash flow risk parameters for a large fraction of the Compustat universe since the 1970s. Fourth, we use our estimates to analyze corporate policies and show that firms with a higher estimated shock correlation implement riskier policies. We also show that the sign of this correlation determines that cash flow sensitivity of cash, as predicted by theory.

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[1] Many cash flow shocks are transitory and do not affect long-term prospects. Examples include temporary changes in demand, delays in customer payments, machine breakdowns, or supply chain disruptions. But long-term cash flows also change over time due to various firm, industry, or macroeconomic shocks that are of permanent nature. Examples include changes in technology or in consumer preferences.

[2] A number of asset pricing papers (see, e.g., Cochrane (1994), Cohen, Gompers, and Vuolteenaho (2002), Bansal, Dittmar, and Kiku (2008), Garleanu, Kogan, and Panageas (2012a), or Garleanu, Panageas, and Yu (2012b)) use such a decomposition to analyze stock returns and risk premia on stocks. This decomposition is also used in market microstructure to analyze price efficiency (see, e.g., Glosten and Harris (1988), Brennan and Subrahmanyam (1996), or Boehmer and Wu (2013)). The literature on income processes also often seeks to decompose shocks into permanent and transitory components; see, e.g., Blundell, Pistaferri, and Preston (2008), Meghir and Pistaferri (2004), or Gottschalk and Moffitt (2009). The decomposition of income shocks between permanent and transitory components has found interesting applications in the life-cycle portfolio choice literature; see, e.g., Cocco, Gomes, and Maenhout (2005). In the time series literature, the permanent-transitory model is known as the unobserved component decomposition, in which the permanent part is the trend and the transitory component is named the cyclical innovation; see Hamilton (1994, Chapter 17).

We begin our empirical analysis by testing whether firm cash flow shocks include a permanent non-stationary component, as assumed in most recent models of investment, financing, liquidity, or compensation policies. To this end, we use two standard unit root tests, the Augmented Dickey–Fuller (ADF) and the Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS) tests, that we implement on the individual cash flows of over 10,000 Compustat firms between 1971 and 2018. Both tests reject stationarity and strongly suggest that a majority of firms operating cash flows are, indeed, subject to permanent shocks.

Assessing the importance of permanent and transitory shocks for corporate policies faces two challenges. First, one needs to be able to identify permanent shocks separately from transitory shocks. Second, one needs to obtain reliable and granular estimates of the cash flow risk parameters to relate these to firm policies. To address these challenges, we estimate a canonical cash flow model that nests as special cases most of the cash flow models used in the recent dynamic investment, financing, liquidity, or compensation (contracting) research. In this model, firm cash flows are subject to profitability shocks that are permanent in nature. In addition, for a given level of profitability, cash flows are subject to short-term shocks, which may be purely transitory or correlated with permanent shocks.[3] Cash flow risk is therefore captured by the firm's exposure to permanent shocks, its exposure to short-term shocks, and the correlation between these shocks. Importantly, positive correlation reduces risk as the firm is more likely to generate positive cash flows after positive productivity shocks have increased firm value. To identify potentially correlated permanent and short-term shocks, we develop a novel Kalman filtering technique that is derived from this theoretical structure. We then use our filtering technique and maximum likelihood to estimate from panel data the parameters driving the cash flow shocks—that is, the volatilities of permanent and short-term shocks as well as their correlation—that best explain observed firm cash flows.

Our estimation of the parameters characterizing cash flow risk yields three striking results. First, we find that permanent and short-term shocks are negatively correlated for most firms,

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[3]In pioneering work, Froot, Scharfstein, and Stein (1993) show that a firm's hedging policy varies dramatically depending on whether price shocks, which are typically short-lived, are positively or negatively correlated with longer-lasting investment opportunities. Correlation between short- and long-term shocks in the literature is indeed generally operationalized by the correlation between investment opportunities and cash flow (see, e.g., Duchin (2010), Acharya, Almeida, and Campello (2007)). Our cash flow model provides an alternative operationalization of this correlation that requires weaker identifying assumptions.

suggesting large hedging needs. Second, we find that firms that are naturally hedged due to a positive shock correlation tend both to choose riskier policies (e.g., take on more debt) and to have lower overall risk than other firms (i.e., have a lower asset or equity volatility and a higher distance to default). By contrast, firms with a higher estimated volatility of permanent or transitory shocks adopt safer policies and yet are riskier. Third, our parameter estimates exhibit remarkable cross-sectional variation. For example, we estimate an interquartile range between 32% and 131% for the permanent shock volatility and between 12% and 60% for the temporary shock volatility. These estimates of volatilities are much more heterogeneous across the Compustat panel than the proxy used in prior research for the precautionary motive to hold cash, namely the industry cash flow volatility (see, e.g., Opler, Pinkowitz, Stulz, and Williamson (1999), Bates, Kahle, and Stulz (2009), or Graham and Leary (2018)). We also show in a major out-of-sample exercise that these estimates can match the actual asset and equity volatilities of the firms in our sample.

Because the estimated parameters characterize cash flow risk and hedging needs, it is natural to explore how they relate to liquidity management policies. Our focus on liquidity management is further motivated by the central role of cash reserves and access to liquidity in ensuring firm resilience to cash flow shocks, as illustrated by the COVID-19 crisis. Due to the precautionary role of cash, models of liquidity management predict that target levels of cash reserves should increase with cash flow risk and hedging needs (see, e.g., Bolton, Chen, and Wang (2011) or Décamps, Gryglewicz, Morellec, and Villeneuve (2017)). In these models, firms build up cash reserves towards their target level either by retaining earnings or by raising outside equity and keeping part of the proceeds in cash reserves. In our empirical analysis, we thus focus on these two separate mechanisms to manage cash reserves. As will become clear, our tests do not require estimating the target level of cash reserves. As a result, they are unaffected by the coefficient biases that stem from trying to measure unobservable variables. Yet, because the predictions that we take to the data take the exact form of the tests that we execute, the connection between theory and tests is tight.

One way for firms to increase their cash reserves and their resilience to shocks is to retain earnings. There is considerable debate in the literature about the sign of the cash flow sensitivity of cash savings. In an influential paper, Almeida, Campello, and Weisbach

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(2004) argue and provide evidence that the sensitivity is positive or zero, depending on firms' financing constraints and hedging needs. Riddick and Whited (2009), by contrast, show that it can be negative with enough persistence in productivity shocks. Décamps et al. (2017) sharpen the prediction and demonstrate that the cash flow sensitivity of cash should be positive when the correlation between permanent and short-term cash flow shocks is positive, and negative otherwise. Indeed, when this correlation is positive, positive (short-term) cash flow shocks are more likely to occur simultaneously with positive (long-term) productivity shocks that increase both firm value and the marginal value of cash and, as a result, firms' incentives to save. We run various tests to verify this prediction and find that the cash flow sensitivity of cash does indeed switch signs depending on the correlation between permanent and short-term shocks. Strikingly, the estimated sensitivities are all highly statistically significant and all exhibit the predicted sign.

Another way for firms to replenish cash reserves is to raise new equity as empirically shown by Kim and Weisbach (2008) or McLean (2011) and theoretically argued in Décamps, Mariotti, Rochet, and Villeneuve (2011) or Bolton et al. (2011). Theory predicts that firms with high permanent or transitory shock volatility should have larger (precautionary) cash reserves and issue larger amounts of new equity. In addition, they should raise equity more frequently. By contrast, firms with a high correlation between permanent and short-term cash flow shocks are more naturally hedged and should therefore hold smaller cash reserves and issue smaller amounts of equity at a lower frequency. Our empirical analysis provides strong support for all these predictions. Notably, focusing on equity issues that lead to an increase in cash reserves, we find a positive and significant relation between the size or frequency of equity issues and the volatility of permanent cash flow shocks. We further find that firms issue less equity when the correlation between short-term and permanent shocks is high. These results are again highly statistically significant and apply both to the size and frequency of equity issues. Our empirical tests additionally show that permanent cash flow volatility is more important than transitory cash flow volatility in explaining the cross-sectional variation in equity issuance activity, demonstrating the importance of incorporating permanent shocks in dynamic corporate finance models.

Our paper relates to the growing theoretical literature on the effects of permanent and

transitory shocks on corporate policies. Gorbenko and Strebulaev (2010) develop a dynamic capital structure model in which cash flows are subject not only to permanent shocks, as in Leland (1998), but also to transitory Poisson shocks. DeMarzo et al. (2012), Hoffmann and Pfeil (2010), Hackbarth, Rivera, and Wong (2020), and, Gryglewicz, Mayer, and Morellec (2020) examine the effects of permanent and transitory cash flow shocks on optimal compensation and investment in dynamic moral hazard models. Décamps et al. (2017) and Bolton, Wang, and Yang (2019) examine the effects of permanent and transitory shocks on cash holdings, credit lines usage, equity issues, and risk management in models with financing frictions. We contribute to this literature by providing efficient estimates of the deep parameters of a cash flow model nesting all of the above, at a granular level and for a large proportion of Compustat firms.

As relevant as it is to analyze the effects of transitory and permanent shocks on corporate policies, there are surprisingly only a few attempts in the empirical corporate finance literature addressing this problem. In an early study, Guay and Harford (2000) show that firms choose dividend increases to distribute relatively permanent cash-flow shocks and repurchases to distribute more transient shocks. Chang, Dasgupta, Wong, and Yao (2014) decompose corporate cash flows into a transitory and a permanent component and show that this decomposition helps understand how firms allocate cash flows and whether financial constraints matter in this allocation decision. Lee and Rui (2007) show that such a decomposition also allows determining whether share repurchases are used to pay out cash flows that are potentially transitory, thus preserving financial flexibility relative to dividends. Guiso, Pistaferri, and Schivardi (2005) examine the allocation of risk between firms and their workers and show that firms absorb transitory shocks fully but insure workers against permanent shocks only partially. Lastly, Byun, Polkovnichenko, and Rebello (2019) examine the separate effects of persistent and transitory shocks on leverage decisions.

Our paper is unique in this class of studies because of the questions it addresses. Another important departure from prior work is that most existing studies use either the Hodrick–Prescott filter or the Beveridge–Nelson decomposition to separate a time series into a trend component and a cyclical (transitory) component. The use of these filters is problematic for our purpose because they cannot handle missing values, which are pervasive in large cash

flow panels, and they cannot estimate the correlations between long- and short-term shocks, which, as we show, can vary widely and influence corporate policies significantly. Our novel Kalman filter is free of these limitations and, as we show, performs much better empirically than these standard filters when applied to corporate cash flows.

Lastly, the type of analysis that relates cash holdings to hedging needs has precedents in the literature, such as Acharya et al. (2007) and Duchin (2010). Our analysis is unique because it uses estimated deep parameters of a canonical cash flow process instead of relying on proxies for cash flow volatility and hedging needs to explain corporate cash policy. Another important difference is that these early studies relate firms' cash holdings to a number of explanatory variables including hedging needs, implicitly assuming that firms are at their target level of cash holdings. Recent theory has shown however that, due to adjustment costs, firms should almost never be at their target cash level (see, e.g., Décamps et al. (2011), Bolton et al. (2011), or Hugonnier, Malamud, and Morellec (2015)). Our paper differs from these early studies because of its focus on specific financing times when the predictions of dynamic liquidity management models are more likely to hold.[4]

The remainder of the paper is organized as follows. Section 1 studies the time series properties of the cash flow data. Section 2 discusses our method to decompose cash flow shocks into permanent and transitory components and estimate their primitive parameters. Section 3 provides firm-specific estimates of the parameters. Section 4 shows how our deep parameter estimates can be used to improve our understanding of liquidity management policies. Section 5 examines the robustness of our empirical results. Section 6 concludes. Technical developments are gathered in the Appendix.

1   Corporate operating cash flows data

We begin our analysis exploring the time series properties of corporate cash flow data. The goal is to understand the nature of firm-level shocks to operating cash flows and to determine which class of models best describe cash flow dynamics.

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[4]Recent studies by Danis, Rettl, and Whited (2012) or Eckbo and Kisser (2020) follow a similar approach to test dynamic capital structure theories.

1.1 Sample

We collect accounting data for publicly traded U.S. firms from Compustat between 1971 and 2018 and stock price data from CRSP. We exclude financial services firms (SIC codes 6000 to 6999), utilities (SIC codes 4900 to 4999) and other regulated firms (SIC codes 8000 to 9999), and firms whose annual asset growth exceeds 500% during the firm's existence in Compustat. We convert all data into 2000 constant dollars using the GDP deflator and winsorize the firm-level variables at the 1st and 99th percentiles.

Unlike panel data studies or most of the structural estimations in the corporate finance literature, our goal is to estimate the deep parameters of the cash flow process with a high level of granularity. To guarantee precision in the estimation, we require firms to have sufficiently long cash flow series. We impose that usable firm has at least ten, not necessarily consecutive, observations. Monte Carlo analysis shows that the precision of our estimates is high when we use at least ten observations per firm, but drops significantly if we include firms with only eight or fewer observable cash flows. The last section of the paper and the Appendix discuss the estimates for firms with little cash flow data and the consequences of restricting the sample to firms with annual asset growth rates below 100% or 200%.

Our final sample includes 208,605 firm-years for 10,136 firms, covering about 43% of the Compustat universe since the 1970s. Our coverage is remarkably high, considering that over 27% of Compustat firms have at most four cash flow observations. To the best of our knowledge, Duchin (2010) is the only other study using individual cash flow moments with almost as many firms. The reason we can achieve such a high coverage owes to an advantageous feature of our Kalman filtering technique: That it does not require consecutive observations.[5] An important implication of this high coverage is that we can also study firms with very volatile cash flows. Such firms are often excluded from empirical studies and yet their behavior is informative. As we shall see, they respond to their very volatile cash flows with conservative policies, leading to much lower asset volatilities.

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[5]Chang et al. (2014) and Byun et al. (2019) are the other two studies that decompose firm cash flows into shocks of different duration. These studies use standard filters requiring arithmetic interpolation, longer time series or no gaps. Hence, they cover at most 5,803 firms (Byun et al. (2019)). We compare the performance of the methods used in these papers to our method of decomposition in Section 2.3.

1.2 The operating cash flows variable

The stochastic properties of the cash flow derived from operations are key determinants of firms' policies, such as earnings retention or external borrowing, that aim to increase cash reserves and, therefore, the firms' resilience to shocks. Hence, we pursue the notion of *Operating cash flows*, defined as EBITDA minus the change in working capital.[6] We subtract the change in working capital because this account captures the allocations of cash that are needed to sustain the firm's operations.[7] The subtraction of the change in working capital (which does not include changes in cash or cash equivalents) is the only difference between our measure and the notion of operating income used in, e.g., Hennessy and Whited (2007). We show in the last section that the estimates of the model parameters do not change significantly if we do not subtract the change in working capital or if we subtract depreciation, which is viewed by Almeida et al. (2004) as a non-discretionary investment required to replace depleted capital.

Our sample includes 10,136 firms that vary along many dimensions. To make firms of different sizes comparable, we divide each year's operating cash flow by the firm's initial value of total assets. Importantly, this normalization does not affect the time series properties of operating cash flows because the initial value of assets is constant over time.

$$\boxed{\text{Insert Table 1 Here}}$$

Table 1 contains the definitions and descriptive statistics of our operating cash flow variable as well as other firm-specific characteristics that we use in the empirical analysis.

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[6]In the savings and investment literature, the maximum cash available to save is approximated by the physical flow of cash from operations minus taxes and interest expenses (Almeida et al. (2004), Denis and Sibilkov (2010), Hennessy and Whited (2007), Riddick and Whited (2009)) and possibly dividends (Opler et al. (1999), Bates et al. (2009)) or extraordinary items (McLean (2011)). Chang et al. (2014) account for *all* flows of cash before investment, including also the net changes in working capital, deferrals, and equity transactions. These definitions are not appropriate for our study as they include a policy choice component.

[7]The working capital account is reported differently in Compustat before and after SFAS #95 regulations. Prior to July 1988, the working capital account is reported directly (wcapc). Afterward, it needs to be constructed using the full statement of cash flows (see Chang et al. (2014)).

1.3 Time series properties of operating cash flows

We run two tests to determine whether operating cash flows include a permanent (non-stationary) component, as assumed in most recent dynamic models of investment, financing, cash savings or compensation policies (see, e.g., Leland (1994), Carlson, Fisher, and Giammarino (2004), Abel and Eberly (2011), DeMarzo et al. (2012), or Décamps et al. (2017)):[8] the Augmented Dickey–Fuller (ADF) test and the Kwiatkowski et al. (1992) (KPSS) test. The null hypothesis in the ADF test is that operating cash flows are non-stationary and have a unit root, while the alternative hypothesis is that they are stationary and follow an autoregressive process with a drift. Given the risk of failing to reject the null hypothesis with small sample sizes, we also implement the KPSS test, in which the null hypothesis is that cash flows are stationary while the alternative is that they follow a unit root process. In KPSS tests, the bias with small samples is towards not rejecting stationarity, i.e., deeming the time series as stationary too often. We run the ADF and KPSS tests for each firm's operating cash flow time series in our panel. Table 2 summarizes the results.

Insert Table 2 Here

The first row in Panel A of Table 2 shows the results for the ADF and KPSS tests over the subsample of 373 firms that have the longest possible cash flow time series of our sample: 48 yearly observations. For 97.1% of the firms in this subsample, in which both tests have the highest power, the ADF test does *not* reject the null hypothesis of non-stationarity at the 1% level. For 91.4% of these firms, the KPSS tests *reject* the null hypothesis of stationary cash flows at the 10% level. The high rejection rate is remarkable for the KPSS test, given that rejecting the hypothesis of stationarity in relatively short samples is typically rare.

The ADF and KPSS tests results also strongly suggest non-stationarity for firms with fewer observations: For 82.8% and 85.1% of all 1,616 firms with at least 30, not necessarily consecutive, cash flow observations, the ADF tests do not reject non-stationarity while the KPSS tests reject stationarity at the 10% level, respectively. Even as the power decreases

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[8]While early dynamic contracting and liquidity models assume that cash flow shocks are purely transitory (see DeMarzo and Sannikov (2006) or Bolton, Chen, and Wang (2011)), recent contributions have enriched these models by adding permanent shocks. See, e.g., He (2009), Hoffmann and Pfeil (2010), DeMarzo et al. (2012), or Gryglewicz et al. (2020) for contracting papers and Décamps et al. (2017) or Bolton et al. (2019) for dynamic liquidity papers.

further, the KPSS tests still reject the hypothesis of stationarity at the 10% level for 70.2% of the 6,342 firms with at least 15 observations in the sample period. (The critical values for the tests cannot be computed for firms with fewer than 15 time series observations.)

In sum, there is overwhelming evidence that a majority of firms' operating cash flows are subject to permanent shocks, as in the most general, canonical cash flow models used in dynamic corporate finance. We now discuss our method to decompose cash flow shocks into permanent and transitory components while estimating said models' primitive parameters.

2 Estimation of the operating cash flows model

2.1 The model

To quantify the exposure of operating cash flows to permanent and transitory shocks, we estimate the discrete time version of a canonical cash flow model. This model nests as special cases most of the cash flow models used in recent dynamic investment, financing, liquidity, or compensation models. In state space form, this cash flow model consists of the following transition and measurement equations:

$$P_t = (1 + \mu)\, P_{t-1} + \sigma_P\, P_{t-1}\, \varepsilon_t^P \tag{1}$$

$$A_{i,t} = P_t + \sigma_A\, P_{t-1}\, \varepsilon_{i,t}^A, \tag{2}$$

where P_t is the unobserved asset productivity with constant growth rate μ and volatility $\sigma_P > 0$, and $A_{i,t}$ is the operating cash flow of firm i, in year t, with short-term volatility $\sigma_A > 0$. This specification implies that the shock ε_t^P influences cash flows permanently by affecting the productivity of assets. The short-term shock $\varepsilon_{i,t}^A$ impacts the cash flow directly and may also affect the firm's long-term prospects. Specifically, we allow short-term and permanent shocks to be correlated with correlation coefficient $\rho \in (-1, 1)$. Hence, the short-term shock can be written as

$$\varepsilon_{i,t}^A = \rho \varepsilon_t^P + \sqrt{1 - \rho^2}\, \varepsilon_{i,t}^T, \tag{3}$$

where $\varepsilon_{i,t}^T$ is a purely transitory shock uncorrelated with ε_t^P. Both ε_t^P and $\varepsilon_{i,t}^T$ are distributed as $\mathcal{N}(0,1)$. When $\sigma_A = \sigma_P = 0$, cash flows follow the Gordon growth model used in textbook valuation models; see, e.g., Berk and DeMarzo (2019). When $\sigma_A = 0$ and $\sigma_P > 0$, cash flows are only subject to permanent shocks. This is the discretized version of the cash flow model used in dynamic investment and capital structure models (see Abel and Eberly (1994) or Leland (1998)). When $\mu = \sigma_P = 0$, cash flow shocks are identically and independently distributed, and follow a purely stationary process, as in early dynamic liquidity or compensation models (see Bolton et al. (2011) or DeMarzo and Sannikov (2006)). When $\sigma_A > 0$ and $\sigma_P > 0$, cash flows are subject to both permanent *and* transitory shocks. When $\rho \neq 0$, the model captures another important dimension of risk. Indeed, ρ reflects the notion of correlation between the firm's current cash flow and its investment opportunities discussed for instance in Froot et al. (1993) and, hence, the firm's hedging needs.

To summarize, equations (1)–(3) capture the heterogeneity of firms' operating cash flow exposures to long-term and short-term risk via different combinations of values of the parameters σ_P, σ_A and ρ.[9] Estimation of this model's parameters with the highest possible level of granularity will enable the testing of empirical predictions that different combinations of parameter values have on corporate policies.

2.2   Estimation

The goal of our estimation is to separately identify permanent and short-term shocks and estimate the cash flow parameters (μ, σ_A, σ_P, and ρ). Because asset productivity is not observable, we represent the cash flow model in the state space form (1)–(2) and estimate the model using the most efficient method, namely maximum likelihood with Kalman filtering. Because shocks are correlated, the standard Kalman filter is biased and inconsistent and, therefore, cannot be used. This problem is reminiscent of an endogeneity issue in regression analysis, with the major difference that the regressor—asset productivity—is unobserved

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[9]This general cash flow model has been proposed by Décamps et al. (2017), who show that cash policy, equity issuance and credit line usage depend on the combination of *all* the cash flow parameters. More recently, a similar cash flow model has been used to explain compensation policy (see, e.g., Gryglewicz et al. (2020)), debt policy (see, e.g., Bolton, Wang, and Yang (2020)), financial development (see, e.g., Rebelo, Wang, and Yang (2020)), or the horizon of corporate policies (see, e.g., Breugem, Marfe, and Zucchi (2020)).

and needs to be filtered out. We solve this problem by theoretically regressing $\sigma_A\,P_{t-1}\,\varepsilon_{i,t}^A$ on $\sigma_P\,P_{t-1}\,\varepsilon_t^P$, and by transforming the measurement equation (2). The new measurement error is then given by the residuals of the above theoretical regression. Because of this transformation, we need to derive a novel Kalman filter that is described in Appendix A.

To provide intuition to our estimation method (which is described in detail in Appendix A), we discuss its steps for the case with no missing observations (Appendix A.3 discusses how missing observations are handled). Using standard notation in state space models, the model in (1)–(2) read as

$$X_t = \Phi_X X_{t-1} + \omega_t \tag{4}$$

$$Z_t = H_Z X_t + u_t, \tag{5}$$

where $X_t = P_t$ is the unobserved state process (latent asset productivity), $\Phi_X = (1+\mu)$, ω_t is the transition shock distributed as $\mathcal{N}(0, \sigma_P^2 X_{t-1}^2)$, Z_t is the observed N-dimensional vector collecting firms' operating cash flows at time t, H_Z is an N-dimensional vector of ones, and u_t is the measurement error distributed as $\mathcal{N}(0, \sigma_A^2 X_{t-1}^2)$. In classic state space models, ω_t and u_t are uncorrelated. In our model, the correlation between permanent and short-term shocks translates into correlated ω_t and u_t. To account for this correlation, we theoretically regress u_t on ω_t and take the residual of this regression as the new measurement error. The measurement equation (5) changes as follows

$$Z_t = H_Z X_t + u_t + J(X_t - \Phi_X X_{t-1} - \omega_t) \tag{6}$$
$$= H_Z^* X_t + \Phi_X^* X_{t-1} + u_t^*,$$

where $H_Z^* = H_Z + J$, $\Phi_X^* = -J\Phi_X$ and $u_t^* = u_t - J\omega_t$. Note that (5) and (6) are equivalent because $X_t - \Phi_X X_{t-1} - \omega_t = 0$. Setting $J = \mathbb{E}[u_t\,\omega_t|X_{t-1}]/\mathbb{E}[\omega_t^2|X_{t-1}]$ yields that the new measurement error u_t^* is uncorrelated with X_t and X_{t-1}. Because the transformed measurement equation depends on X_{t-1}, the prediction step of Z_t and its error covariance matrix are different than in the standard Kalman filter. This difference leads to the generalized Kalman filter derived in Appendix A.2. We note that this method does not involve any

approximation of the model in (1)–(3). If $\rho = 0$, then $J = \Phi_X = 0$ and $H_Z^* = H_Z$, and the generalized Kalman filter reduces to the standard Kalman filter.[10]

Finally, given the model parameters ρ, σ_P, σ_A, μ, the generalized Kalman filter recovers the unobserved state process X_t that determines the likelihood function of observed cash flows Z_t, $t = 1, \ldots, T$,

$$\sum_{t=1}^{T} -\frac{1}{2} \left[N \log(2\pi) + \log |F_{t|t-1}| + (Z_t - \hat{Z}_{t|t-1})' F_{t|t-1}^{-1} (Z_t - \hat{Z}_{t|t-1}) \right], \tag{7}$$

where $Z_{t|t-1}$ is the one-step-ahead prediction of Z_t based on the filtered state process X_t and X_{t-1}, and $F_{t|t-1}$ is the error covariance matrix defined in (A8). Model parameters are changed so as to increase the value of the log-likelihood, which requires re-running the generalized Kalman filter and re-computing the log-likelihood. The iterative procedure is repeated until convergence, which takes less than one second for a cash flow panel of $N = 10$ firms observed over $T = 48$ years. A Monte Carlo analysis, described in Appendix B, confirms that our generalized filter outperforms the standard Kalman filter, in which $\rho = 0$.

2.3 Comparing methods to recover shocks

Our generalized filter offers four main benefits over standard methods to separate a time series into a trend (persistent) component and a cyclical (transitory) component, such as the Hodrick–Prescott (HP) filter and the Beveridge–Nelson (BN) decomposition.[11]

First, neither of these standard filters is suited to study correlations between permanent and short-term shocks. The HP filter assumes zero correlation between trend and cyclical components, whereas the BN decomposition imposes perfectly correlated trend and cyclical

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[10]Our method to handle the correlation between transition and measurement errors can be applied to general state space models, in which for example the state process X_t is vector valued. In that case, $J = \mathbb{E}[u_t \, \omega_t' | X_{t-1}] \mathbb{E}[\omega_t \, \omega_t' | X_{t-1}]^{-1}$, where $'$ denotes transposition. Properly accommodating correlated transition and measurement errors can be an important aspect in applications of state space models in other fields.

[11]In the empirical corporate finance literature, the Hodrick–Prescott filter has been applied for instance by Byun et al. (2019) and the Beveridge–Nelson decomposition by Chang et al. (2014). Given a time series $y_t, t = 1, \ldots, T$, the HP and BN filters provide the additive decomposition $y_t = \tau_t + c_t$, where τ_t is identified as a trend component and c_t as a cyclical component. In the HP filter, the trend component $\tau_t, t = 1, \ldots, T$, is obtained as the minimization of $\sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1}((\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}))^2$, where the parameter $\lambda > 0$ controls the smoothness of the trend component. The BN filter is based on an ARMA model for $(y_t - y_{t-1})$ and identifies the trend component τ_t as a random walk with drift.

shocks. This aspect is problematic because the shock correlation is key to capture firms' hedging needs. Second, neither is designed to recover volatilities of permanent shocks. As shown with formal tests in Section 1, permanent shocks are a major driver of firms' cash flows. Third, neither can handle missing observations. These methods were developed to decompose complete time series such as annual consumption or GDP. By contrast, Kalman filtering is by design a method of estimation and imputation of missing data (see Appendix A.3 for details). Many Compustat firms have holes in the cash flows time series. Because of these missing data, applying the HP or BN filter would force us to drop more than half of the 10,136 firms in our panel. Fourth, our method provides a decomposition while estimating the deep parameters of a canonical cash flow model. With other filtering methods, deep parameters can only be approximated with the calculation of time-varying moments over time series of filtered shocks.

To illustrate the benefits of using our method to recover cash flow shocks from uninterrupted cash flow time series (i.e., to illustrate benefits 1 and 2 above), we run a Monte Carlo simulation that consists of the following steps: (i) simulate one panel of cash flows for 10 firms over 50 years using the model (1)–(3) with the parameter values in Décamps et al. (2017), i.e., $\rho = -0.21$, $\sigma_P = 0.25$, $\sigma_A = 0.12$, $\mu = 0.01$; (ii) estimate the four model parameters using our method in Section 2.2, which we label as KF. For the HP and BN methods, (iii) apply the filter to each time series of cash flows to recover trend and cycle components at the firm level (using an adjusted smoothing parameter $\lambda = 6.25$ as in Byun et al. (2019) for the HP filter and an ARMA(2,2) model as in Chang et al. (2014) for the BN filter); (iv) compute the correlation between trend and cycle shocks and their standard deviations to obtain estimates of ρ, σ_P, σ_A, and the mean of trend changes to obtain μ; (v) average these estimates across the 10 firms; (vi) compute the estimation errors, defined as estimated values minus true parameter values, for KF, HP, and BN; (vii) repeat the procedure above 1,000 times.

Insert Figure 1 Here

Figure 1 summarizes the simulation results. The HP and BN methods are systematically biased and vastly inaccurate. While KF can be expected to outperform HP and BN, as KF estimates the model which is used to simulate the cash flow data, HP and BN produce largely

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imprecise estimates on their own. A well-known limitation of the BN decomposition is that the correlation between trend and cyclical shocks is either $+1$ or -1 depending on the ARMA parameters, as BN relies on a one-shock-only ARMA model. Consequently, BN is unable to estimate the correlation ρ. The HP filter imposes zero correlation and nearly always overestimates the true negative correlations, with a median bias of 0.35. While HP tends to outperform BN, both methods substantially underestimate the volatility σ_P of permanent shocks and the drift μ, and largely overestimate the volatility σ_A of short-term shocks. For example, the true value of σ_P is 0.25, while HP gives median estimates of 0.07 only. The KF method produces unbiased and accurate estimates of all four parameters.

$$\boxed{\text{Insert Figure 2 Here}}$$

Figure 2 provides an illustrative example of the performance of KF and HP.[12] For a simulated panel of cash flows, the figure shows the time series trajectory of the latent asset productivity (known in simulation), the Kalman-filtered asset productivity, and the HP-filtered trend component. The HP filter produces an estimated trajectory of the asset productivity that is too smooth, precisely because the HP filter is a cubic spline smoother. Taking the HP-filtered trend component as latent asset productivity would lead to significant underestimation of the volatility of permanent shocks; see for instance Hamilton (2018) for a recent discussion of the drawbacks of the HP filter. In contrast, the Kalman-filtered asset productivity tracks closely the true asset productivity.

In unreported Monte Carlo simulations, we draw the parameter values of $\rho, \sigma_P, \sigma_A, \mu$ from uniform distributions spanning the interquartile range of the parameter estimates reported in Table 4. In that case, simulated cash flows are more volatile than the above cash flows. Consequently, estimation errors of HP and BN are much larger than those in Figure 1, whereas KF provides precise estimates of all model parameters.

2.4 Identifying assumptions

If there was no correlation between the shocks ($\rho = 0$), the cash flow model in (1)–(3) would be a classic state space model with Gaussian likelihood. The remaining three parameters

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[12]Because HP outperforms BN, we do not report the latter in Figure 2 for readability.

would be identified from the unique global maximizer of the likelihood function (see Appendix B for details). To identify the shock correlation, this model assumes that transitory shocks are firm-year specific while permanent shocks have a "systematic" nature, i.e., that they are common to all firms in a set of equal asset productivity as in, e.g., Cocco, Gomes, and Maenhout (2005). Indeed, correlated permanent and short-term shocks are not identified if both shocks are firm-specific.

To provide an intuition for this identifying assumption, consider a conventional model of asset productivity in which an observable process is driven by the sum of persistent shocks (modeled as an AR(1) process) and short-term shocks (modeled as a white noise process). When both shocks are unobservable, the challenge of identifying their correlation is similar to identifying the correlation ρ in (1)–(3). As we formally show in Appendix A.4, the correlation between firm-specific persistent and short-term shocks is not identified because this parameter enters *all* autocovariances of the observed firm productivity as a multiplicative constant to *both* persistent and short-term volatilities, and thus the correlation cannot be disentangled from the volatilities.[13] If instead, persistent shocks are common across firms, as per our identifying assumption, then the time series of the cross-sectional average productivity provides additional and non-redundant moment conditions to identify the shock correlation. In essence, the common persistent shock has the interpretation of a "systematic" cash flow factor, as in the classic factor models that are routinely estimated in the empirical asset pricing literature.

The implication of this result is that the firm-by-firm estimation of the model in (1)–(3) is infeasible. Individual firm estimation is also undesirable because annual cash flow time series are not very long. Our solution to achieve maximum granularity is to estimate the model parameters for the smallest possible groups of firms, assuming each firm in the group is exposed to the same permanent shocks. Effectively, this assumption is significantly weaker than a common practice to assume that long-term productivity shocks are common to *all* firms in an industry. For example, Bates et al. (2009) use the volatility of the average cash flow over all firms in each two-digit SIC code. Similarly, Acharya et al. (2007) and Duchin

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[13]A proof that the shock correlation in (1)–(3) is not identified when permanent shocks are firm-specific is beyond the scope of this paper given that the model features a multiplicative, non-stationary process.

(2010) operationalize the firm's hedging needs with the correlation between a firm's current cash flow and the median or mean R&D expense over all firms with the same three-digit SIC code. As we shall see next, our estimation can achieve a very high level of precision with only ten firms per group, rendering our commonality assumption almost innocuous.

2.5 Grouping firms with similar cash flow dynamics

We estimate the cash flow model in (1)–(3) for each of *many* small groups of firms. We assume that all firms within each group are homogeneous in that they have the same parameters $\mu, \sigma_P, \sigma_A, \rho$, and asset productivity, P_t. Fitting the model to relatively small samples allows us to achieve greater estimation accuracy because the model parameters can adjust to the data features of each specific group of firms. Moreover, we obtain a large set of estimates of the cash flow model's deep parameters, as opposed to just one or a few sets for their representative firms. Since the limiting case—which is to estimate the cash flow model firm-by-firm—is not feasible, estimation by small groups maximizes the cross sectional variation in these estimates and enables a direct test of the predicted link between deep parameter heterogeneity and corporate policies.

To group firms, we adopt two sequential criteria that are motivated by the assumption that permanent shocks are common to all firms in the group. The first is the three-digit SIC industry code. We expect firms within the same three-digit SIC industry to be exposed to similar short-term volatility (e.g., industry demand uncertainty) and similar permanent shocks (e.g., technology or regulatory shocks). The second is the firm's cash flow growth rate: Within each three-digit SIC industry, we group firms based on their average annual growth rate of cash flows. In the long-run, firms with similar asset productivity will have similar average cash flow growth rates. For the precision of our parameter estimates, based on the simulation evidence in Appendix B, we impose the additional requirement that each group includes at least 10 firms. Because the number of firms in any given industry is not generally a multiple of 10, the last group of firms in each three-digit SIC code will include between 10 and 19 firms.

Insert Figure 3 Here

Applying the criteria above, our sample of 10,136 firms is split into 918 SIC3-cash flow growth groups. As an example, Figure 3 shows the cash flows of one group of firms in the 100 SIC code. Missing observations in firm cash flows are evident in the interrupted time series of firm cash flows. Because our groups are relatively small, our parameter estimates can potentially exhibit substantial variation even within three-digit SIC industries.

To assess the homogeneity of firms within each group, we decompose the total variation of several firm-specific outcome and policy variables into the between- and within-group components. For each characteristic, we compare the similarity within and heterogeneity between our estimation groups to those implied by other narrow industrial classifications. Table 3 shows that, relative to the four-digit SIC or the 17 Fama and French (1997) industries, our classification produces less *within-group* variation for the ratios of annual sales-to-assets, earnings-to-assets, and average sales growth, as well as for key policy variables such as cash holdings, the rates of savings and equity issuance, the size of the credit lines (relative to total debt), the capex-to-assets and debt-to-assets ratios. Our grouping also implies more within-similarity in the ratio of R&D expenditure to sales, the markups estimated following De Loecker, Eeckhout, and Unger (2018), the number of patents and their market value, according to Kogan, Papanikolaou, Seru, and Stoffman (2017). Remarkably, grouping only by long-run similarity in the average cash flow growth rate within each three-digit SIC industry produces similarities across many other dimensions.

Insert Table 3 Here

Table 3 shows that our grouping method also produces the most *between-group* variation for as many firm characteristics relative to the four-digit SIC or the 17 Fama and French (1997) industrial classifications. In a nutshell, our grouping approach produces many small and heterogeneous groups of alike firms. The implied high granularity of estimates is key for hypothesis testing or calibration of dynamic models.

3 Cash flow model estimation: Results

Table 4 summarizes the Maximum Likelihood (ML) estimates of the model's four parameters, μ, σ_P, σ_A, and ρ, for all the 918 three-digit SIC-cash flow growth rate groups (Panel A), their

precision (Panel B), and the correlation between the parameter estimates (Panel C). We winsorize the estimates at the 1st and 99th percentiles when they approach their respective lower and upper bounds (i.e., near -1 and 1 for the shock correlation, and near zero for each volatility), and at 10th and 90th percentiles otherwise.

Insert Table 4 Here

3.1 Estimates of ρ

The estimates of the correlation between permanent and short-term shocks in Panel A exhibit significant variation across groups. The 5th percentile of the estimated correlations is -0.23 while the 95th percentile is 0.23 (with a minimum of -0.34 and a maximum of 0.58, unreported). The median estimated correlation is -0.076, with 80% of the estimates being negative. As shown in Section 4, this estimated correlation implies, for example, that the median firm issues 5.5% more net equity than a firm with an estimated correlation of zero. Panel B additionally shows that close to 56% of the estimated ρ are significantly different from zero with 95% confidence.

A unique feature of cash flow models that include correlated permanent and short-term shocks is that liquidity policies depend crucially on the sign of the correlation between the two shocks. Our framework enables the testing of such unique predictions because our estimates of ρ exhibit significant sign heterogeneity.

3.2 Estimates of σ_P and σ_A

The estimates of the volatility parameters in Panel A also exhibit significant variation across groups. The median estimated permanent shock volatility, $\hat{\sigma}_P$, is 65.1%. The total standard deviation of 58% is explained mostly by within rather than between three-digit SIC variation. Recall that, to have maximum coverage of Compustat, we only exclude firms with annual asset growth rates above 500%. Hence, we can estimate and report the magnitudes of the highest permanent shocks volatilities in the Compustat universe. To wit, the estimates of $\hat{\sigma}_P$ exceed 126% for 25% of the firms. The median estimated short-term shocks volatility, $\hat{\sigma}_A$, is 9.3%. Estimates also vary significantly within the three-digit SIC classification and

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include very high values for 5% of the groups. We show in Appendix C that our estimates imply asset volatilities that are comparable to those of actual Compustat firms.

3.3   Estimates of μ

The estimates of μ exhibit an interquartile range from 6.4% to 21.8%, with an average productivity growth of 14.8%. Almost 50% of the estimates are significantly different from zero with 95% confidence. These estimates also show that our grouping procedure captures important differences in latent productivity growth rates across and within industries.

3.4   Understanding the estimates: Permanent shocks volatilities

Our cash flow model and filtering technique interpret the very high cash flow volatilities in the data as rather moderate volatilities of permanent and transitory shocks. Indeed, in our sample, the median of the standard deviations of annual cash flow growth is a very high 210%. Yet our model infers median estimate of σ_P and σ_A of 65.1% and 9.3%, respectively.

To understand why our model makes such inference, consider how σ_P is identified. Let $\overline{A}_t$ denote the cross-sectional average cash flow within each group of $N = 10$ firms, i.e., $\overline{A}_t = \sum_{i=1}^{N} A_{i,t}/N$, for $t = 1, \ldots, T = 48$ years. Let R_t denote the relative change of $\overline{A}_t$. This observable rate is approximately equal to the relative change of the unobservable P_t (with equality if $N \to \infty$, and $\rho = 0$ or $\sigma_A = 0$), i.e.,

$$R_t \equiv \frac{\overline{A}_t - \overline{A}_{t-1}}{\overline{A}_{t-1}} \approx \frac{P_t - P_{t-1}}{P_{t-1}}. \tag{8}$$

To illustrate, Figure 3 shows $\overline{A}_t$ superimposed to firm cash flows for a select group of low-correlation firms ($\hat{\rho} = 0.1$): The time series trajectory of $\overline{A}_t$ mimics the filtered asset productivity $\hat{P}_t$ for this group. Absent short-term shocks ($\varepsilon_{i,t}^A = 0$), the time series standard deviation of R_t would be approximately equal to σ_P, as $A_{i,t} = P_t$ in (2). In general, the approximation in (8) implies that the estimated volatility of permanent shocks is expected to be positively related to, albeit smaller than, the time series standard deviation of R_t.

Insert Figure 4 Here

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Figure 4 shows the scatter plot of the time series sample standard deviations of R_t against model-inferred volatilities of permanent shocks, $\hat{\sigma}_P$, for the 918 groups in our sample. As predicted, this figure shows a strong positive association between standard deviations of R_t and the estimates of σ_P, providing direct evidence that our estimates of σ_P are capturing the volatility of permanent shocks. Moreover, standard deviations of R_t are generally larger than the estimates of σ_P, meaning that short-term shocks are present in cash flow data.

3.5 Understanding the estimates: Cash flow shock correlation

To the best of our knowledge, there exist only two previous attempts (i.e., Duchin (2010) and Acharya et al. (2007)) in the literature to operationalize the notion of correlation between current cash flow and investment opportunities. Our estimates are the first to directly target the notion of hedging needs by way of a deep parameter of a dynamic cash flow model. Our estimates differ from those in the literature. Most importantly, Duchin (2010) and Acharya et al. (2007) report mostly positive correlation between current cash flow and investment opportunities whereas we obtain mostly negative estimates of ρ. [14] An important reason for these measurement differences may be that previous proxies assume that a firm's investment opportunities are given by its industry mean or median R&D expense. Our approach does not require a proxy for the state of industry technology based on a policy variable. We are also agnostic about which firm may lead the state of technology in the industry. Under the mild assumption that technology is common to a group of only ten firms, we find significant within three-digit SIC variation in $\hat{\rho}$, with an important proportion of negative estimates, i.e., high hedging needs.

An important question is which industry or firm characteristics are associated with variation in the estimates of ρ, with the objective to understand the deeper differences across firms that are captured by our estimates. Indeed, the sign and magnitude of shock correlations may be a technological characteristic intrinsic to each industry. For example, Froot et al.

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[14]Duchin (2010) reports a median cash-flow-investment opportunities correlation of 0.25, i.e., a large majority of firms with a *positive* correlation and, hence, low hedging needs. Acharya et al. (2007) do not report a summary, but one can infer that about 39% of firm-year observations have a correlation higher than 0.2 (the 'Low hedging needs' subsample). Although not the focus of their paper, Chang et al. (2014) report a negative realized correlation of -0.21 between the trend and cycle components of cash flow, although theoretically their BN decomposition assumes a correlation of -1.

(1993) conjecture that technologies requiring different degrees of operating leverage may lead to different sensitivities of investment opportunities to demand shocks and, therefore, different hedging needs.

<div align="center">Insert Table 5 Here</div>

Table 5 explores these conjectures. The table shows that the distributions of the estimates of ρ across all the 17 Fama–French industries (FF17) are remarkably similar: All of the medians are negative, ranging between -0.10 and -0.06. Except for four FF17 industries, fewer than 25% of the firms in each industry have a positive ρ. However, at least 5% of firms in each FF17 industry have a positive ρ. For most industries, there exist small groups of firms with significantly high positive estimates of ρ (Figure 5). In sum, the estimates of ρ, which have been obtained independently for small groups of firms within each industry, have very similar distributions across very different industries.

<div align="center">Insert Figure 5 Here</div>

Next, we ask whether the estimated correlations are associated with policy choices and outcome variables *within* each industry. Table 6 reports the average Spearman's rank correlation coefficients between the estimates of ρ and variables capturing risk choices and risk measures. All ranks and correlations are computed annually by industry and reported as an average over all industry-years. We compute the rank correlations for different industry definitions: Three- and four-digit SIC codes, and the 17 Fama–French industries.

<div align="center">Insert Table 6 Here</div>

Table 6 highlights several interesting results. First, firms that are naturally hedged due to a positive shock correlation tend both to choose riskier policies and to have lower overall risk than other firms. Notably, the within-industry comparisons reveal that firms with the highest estimated shock correlations tend to have the largest capital-to-labor ratios, operating leverage, debt-to-asset ratios, and acquisition-to-asset ratios within their industry. Yet, despite these riskier policy choices, these firms also tend to have lower default risk (as measured using Bharath and Shumway (2008) distance to default), lower loan spreads

<div align="center">22</div>

(despite higher loan maturities), lower equity volatility, and lower asset volatility. The results are robust to fine (SIC3, SIC4) or broad industry definitions (FF17). Second, firms with higher exposure to permanent or transitory shocks choose more conservative policies but have higher overall risk. This again applies to all the policy choices and risk measures we look at and to all industry definitions. Importantly, while Table 6 is mostly concerned with correlations, Section 4 goes one step further by showing how our deep parameter estimates can explain the dynamics liquidity management.

4 Cash flow model parameters estimates: Applications

This section shows how our deep parameter estimates can be used to improve our understanding of firm policies. Because the estimated parameters characterize cash flow risk, it is natural to explore their effects on policy choices that increase the resilience of firms to shocks, such as liquidity management. Recent dynamic liquidity management models firms predict that firms build up cash reserves towards their target level either by retaining earnings or by raising outside equity and keeping (part of) the proceeds in cash reserves (see, e.g. Bolton et al. (2011), Bolton, Chen, and Wang (2013), or Décamps et al. (2017)). In our empirical analysis, we thus focus on these two separate mechanisms to manage cash reserves. In the first part of the section, we use our estimates to resolve the debate on the sign of the cash flow sensitivity of cash savings. In the second part, we demonstrate how our estimates of cash flow risk parameters relate to firms' decisions to issue equity to rebuild cash buffers.

4.1 Cash savings

One way for firms to increase their cash reserves, and thus their resilience to shocks, is to retain part of their earnings. There is considerable debate in the literature as to whether the sign of the cash flow sensitivity of cash is positive or negative. In an influential paper, Almeida, Campello, and Weisbach (2004) theoretically argue and provide evidence that the sensitivity is positive, if the firm is financially constrained, or zero. Riddick and Whited (2009), by contrast, show that it can be negative if productivity shocks are sufficiently persistent. Décamps et al. (2017) sharpen the prediction in their dynamic model, in which

the cash flow sensitivity of cash is proportional to $\rho \times \frac{\sigma_P}{\sigma_A}$. That is, they demonstrate that the sign of the cash flow sensitivity of cash is equal to the sign of ρ and that its absolute value should be higher for higher ratios of σ_P/σ_A.[15] Using our parameter estimates, we can directly test this prediction and resolve this unsettled debate in the literature.

To analyze how the cash flow sensitivity of savings depends on hedging needs and the volatilities of cash flow shocks, we estimate the cash flow sensitivity of cash over several subsamples formed using our estimates of ρ and σ_P/σ_A. We first partition our sample based on the estimates $\hat{\rho}$. Because of estimation error in $\hat{\rho}$, we do not choose zero as the exact switching threshold of the cash flow sensitivity. Instead, we perform the tests over the subsamples of firms with $\hat{\rho}_i \leq -0.03$ (covering 73% of our sample firms) and $\hat{\rho}_i \geq 0.03$ (covering an additional 16% of our sample firms). For robustness, we also perform the tests over the subsamples $\hat{\rho}_i \leq -0.02$ and $\hat{\rho}_i \geq 0.02$, covering 92% of our sample firms.

Sensitivity sign differences would be most clearly detected among firms with higher absolute sensitivities. Hence, we estimate the cash flow sensitivities of cash over increasingly restrictive subsamples based on the distribution of the ratio σ_P/σ_A, with values above the median, the 60th percentile, or the 70th percentile. The results are robust to measurements in the top tercile or quartile. For each of the resulting six subsamples (combining two sets of values for $\hat{\rho}$ and three sets for $\hat{\sigma}_P/\hat{\sigma}_P$), we estimate the cash savings regression in Almeida et al. (2004) and Riddick and Whited (2009):

$$Cash\ savings_{i,t} = \beta_0 + \delta_t + \beta_{CF} \times Cash\ flow\text{-}to\text{-}assets_{i,t} + \boldsymbol{\beta}_{\text{Controls}} \times \mathbf{Controls}_{i,t-1} + u_{i,t} \quad (9)$$

in which *Cash savings* is the yearly change in the stock of cash divided by total assets. Control variables include the *Market-to-book ratio* and ln(*Total assets*).

Riddick and Whited (2009) note that this regression includes the *Market-to-book ratio*, i.e., average Q, as a proxy for marginal q. As a result of measurement error in this variable,

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[15]The intuition for this result builds on the observation that higher productivity leads to a higher marginal value of cash and thus an increased propensity to save. The relation between productivity shocks and cash flow shocks depends on the sign of ρ. In firms with positive ρ, a positive cash flow shock coincides on average with a positive productivity shock and leads to increased cash savings. Thus positive ρ is associated with a positive cash flow sensitivity of cash. The opposite occurs for negative ρ. When σ_P is large relative to σ_A, then shocks to the propensity to save cash (proportional to productivity shocks and σ_P) are large relative to cash flow shocks (proportional to σ_A).

the OLS estimator of the propensity to save is biased towards zero. Consistency is achieved by additionally matching higher moments of the joint distribution of the dependent variable, *Cash savings*, and average Q. Therefore, we follow Riddick and Whited (2009) and estimate the propensity to save using the fourth-order linear cumulants estimator (LC4) of Erickson, Jiang, and Whited (2014). Table 7 presents these estimates.

$$\boxed{\text{Insert Table 7 Here}}$$

The prediction that the cash flow sensitivity of cash switches sign () is most clearly observed in the subsample of relatively high $\hat{\sigma}_P/\hat{\sigma}_A$ ratios (i.e., the top 30%). In this subsample, the estimated sensitivity, β_{CF}, is negative and statistically significant when $\hat{\rho}_i \leq -0.03$ but positive and statistically significant when $\hat{\rho}_i \geq 0.03$. The estimated sensitivity remains negative for $\hat{\rho}_i \leq -0.02$ and positive for $\hat{\rho}_i \geq 0.02$, confirming that the switching of sign in the propensity to save is not driven by observations when $\hat{\rho}$ may be close to zero. Remarkably, the estimated sensitivity, β_{CF}, exhibits the predicted sign switch for all of the 12 sets of test partitions. That is, we find that hedging needs (i.e., ρ) are a defining feature of the cash flow sensitivity of cash.[16]

4.2 Equity issues

Another way for firms to replenish cash reserves is to raise outside funds by issuing equity, as empirically shown by Kim and Weisbach (2008) or McLean (2011). Issuance costs of securities generally deter firms from continuously raising funds to be at their target cash level. Instead, firms remain inactive (away from their target) for long spells until the benefits of raising funds to increase cash reserves out-weigh the costs. Testing dynamic liquidity models thus requires distinguishing points at which firms are at (or move to) their target level of cash reserves from points at which they are not. To isolate such optimality points, we examine periods when firms simultaneously raise outside funds (by issuing either debt or equity) and increase their cash reserves. The optimality of such increases in cash reserves follows directly from dynamic inventory models because these refinancing points reflect optimal

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[16]Estimation by OLS yields the same qualitative results: the sign of the propensity to save equals the sign of $\hat{\rho}$ and its magnitude increases with the ratio $\frac{\hat{\sigma}_P}{\hat{\sigma}_A}$. Confirming attenuation bias, the OLS estimates are smaller in magnitude than the LC4. These results are available upon request.

liquidity choices (see, e.g., Bolton et al. (2011) or Décamps et al. (2017)). Additionally, and as discussed in Danis et al. (2012), "large decisions likely follow considerable deliberation, so it is hard to imagine that managers view these adjustments as suboptimal."

Dynamic liquidity management models not only predict that firms will adjust their cash buffer infrequently but also that the frequency and size of the adjustments should be related to cash flow characteristics. For instance, theory predicts that firms with high permanent or transitory shock volatility should hold, on average, larger cash reserves and issue larger amounts of debt and equity. In addition, they should raise external funds more frequently. By contrast, firms with a high correlation between permanent and short-term cash flow shocks, which are naturally hedged, should hold smaller cash reserves and issue smaller amounts of debt and equity, and do so less frequently.[17]

To analyze the relation between the estimated cash flow risk parameters ($\hat{\rho}$, $\hat{\sigma}_P$, and $\hat{\sigma}_A$) and equity issuance, we use a standard liquidity regression model (as in, e.g., McLean (2011)) that we augment with our estimated parameters and implement using the methodology described above:

$$Y_{i,t} = \beta_0 + \delta_t + \gamma_j + \beta_\rho \times \hat{\rho}_g + \beta_{\sigma_P} \times \hat{\sigma}_{P,g} + \beta_{\sigma_A} \times \hat{\sigma}_{A,g} + \boldsymbol{\beta}_{\text{Controls}} \times \mathbf{Controls}_{i,t-1} + u_{i,t}. \quad (10)$$

We use the subscripts i for firms, g for groups of firms, and t for years. The dependent variable is either i) gross equity issues scaled by lagged assets (*Gross equity issuance*) as in McLean (2011), ii) gross equity issuance minus dividends and share repurchases scaled by lagged assets (*Net equity issuance*), iii) a dummy variable equal to one if *Gross equity issuance* is larger than 5%, and zero otherwise (*Equity issuance dummy*) or iv) a dummy variable equal to one if *Net equity issuance* is larger than 5%, and zero otherwise (*Net equity issuance dummy*). To capture the instances when firms are likely to channel the proceeds from equity issues to cash reserves, we estimate these regressions using the subsample of

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[17]These firms have low hedging needs because low (high) short-term cash flows tend to occur only when productivity is declining (improving) (see, e.g., Froot et al. (1993), Morellec and Smith (2007), or Décamps et al. (2017)). The type of analysis that relates cash holdings to hedging needs has precedents in the literature, such as Acharya et al. (2007) and Duchin (2010). Our analysis is unique because it uses estimated deep parameters of a canonical cash flow process instead of relying on proxies for cash flow volatility and hedging needs to explain corporate cash policy. Our paper also differs from prior work because of its focus on specific refinancing times when theory is more likely to hold.

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firm-years where firms experience a *positive* change in the cash-to-asset ratio (the sample median of the cash-to-asset ratio is zero) in that year. The results are robust to restricting the sample to firm-years in which the change in the cash-to-asset ratio is in the top tercile or in the top quartile of the cash-to-asset sample distribution.

As in, e.g., Bates et al. (2009), we control for the lagged *Industry cash flow volatility*, which varies yearly at the two-digit SIC industry, for firms' growth opportunities with the residuals of the lagged market-to-book ratio (*Market-to-book ratio*),[18] for lagged cash flow (*Cash flow-to-assets ratio*), and for lagged firm size (ln(*Total assets*)).[19] We include year fixed effects (δ_t) to control for time-specific shocks that affect all firms. Because our estimates of ρ, σ_P, and σ_A are constant over time (as assumed in the theoretical literature) but vary across the 918 groups used for the cash flow model estimation, we cannot include firm fixed effects in these regressions. However, the parameter estimates exhibit substantial within industry variation. We therefore include two-digit SIC industry fixed effects (γ_j) to absorb time-invariant industry effects. Because equation (10) uses estimates of ρ, σ_P, and σ_A, we calculate the standard errors conservatively by bootstrapping the standard errors and by clustering at the three-digit SIC level.

Table 8 presents the results. Columns 1 and 2 show the results for *Gross equity issuance*. The estimates of β_ρ are negative and significantly different from zero in both columns, consistent with the predictions of liquidity management models. The estimates are also economically significant. A one sample standard deviation increase in the estimated correlation between short-term and permanent shocks ($\hat{\rho}$) is associated with a decrease in *Gross equity issuance* of 6.2% relative to the sample mean. That is, firms with high hedging needs issue significantly larger amounts of equity. In columns 3 and 4, the dependent variable is the *Gross equity issuance dummy*. The estimates of β_ρ are also negative and statistically significant, suggesting that firms with high hedging needs not only issue larger amounts of equity, but do so more frequently. We obtain very similar results using *Net equity issuance*

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[18]Controlling for the market-to-book ratio, which is typical for such regressions, is problematic in our context because, in theory, Tobin's Q is a function of the cash flow shock volatilities, their correlation, and the growth rate. To address this problem, all specifications control instead for the residuals of the regression of the *Market-to-Book ratio* on $\hat{\rho}$, $\hat{\sigma}_P$, $\hat{\sigma}_A$, and $\hat{\mu}$.

[19]The results are robust to the inclusion of other control variables such as net working capital, capital expenditures, R&D, leverage, and dividends.

(columns 5 and 6) and *Net equity issuance dummy* (columns 7 and 8). To our knowledge, our paper is the first that relates hedging needs to the firms' equity issuance activity in a dynamic setting.

Insert Table 8 Here

All eight columns also show a positive and significant relation between equity issues (gross and net, size and frequency) and permanent cash flow shocks volatility. The economic magnitudes are sizeable. For example, in column 1, a one sample standard deviation increase in the estimated permanent volatility ($\hat{\sigma}_P$) is associated with a increase in *Gross equity issuance* of 13.7% relative to the sample mean. In six of the eight columns, the short-term cash flow shocks volatility is also positively associated with equity issues. The economic magnitudes, however, are smaller when compared with permanent cash flow shocks volatility. Our tests therefore suggest that permanent cash flow shocks are more important than transitory cash flow shocks in explaining the cross-sectional variation in equity issuance activity. Our findings for cash flow volatility are consistent with McLean (2011), who shows that firms issue equity to replenish cash reserves for precautionary reasons. However, we note that *Industry cash flow volatility* is *not* systematically related to equity issuance activity. That is, the variation in cash flow risk explained by our estimates of the three deep parameters subsumes and improves the explanatory power of the traditional proxy. Finally, firm size and the cash flow to assets ratio are negatively related to equity issuance activity, while the market the book ratio is positively related.

Overall, our cash flow risk parameter estimates are related to equity issuance as predicted by theory. Firms that are naturally hedged (high ρ firms) issue less equity and do so less frequently. Our findings also shed new light on the relative importance of permanent and short-term shocks for liquidity policies. Notably, permanent cash flow shocks volatility seems to have economically larger effects on equity issues than short-term shocks volatility.

5 Robustness

5.1 Selection issues

Our filter has the ability to deal with missing cash flow observations and, as a result, our sample has the maximum possible coverage of Compustat firms with at least ten, not necessarily consecutive, cash flow data points. Additionally, it would be possible to classify up to 7,239 more firms with eight or nine available observations into one of our estimation groups. Imputing the group parameter estimates to each of these firms virtually implies the same distribution of parameter estimates in the larger sample, which covers 73% of the firms in the Compustat universe.

Our range of estimates is not representative of the very short-lived firms in Compustat. We use simulation to try to understand the range of parameter values that these firms may have. Using the Décamps et al. (2017) model (summarized in the Appendix C) we have confirmed that firms with relatively high ρ outlast otherwise similar firms with the lowest values of ρ, despite the fact that high ρ firms may simultaneously experience negative productivity and short-term shocks. Again, high ρ firms have a natural hedge advantage in that low (high) short-term cash flows tend to occur only when productivity is declining (improving) and the firm has lower (higher) needs for cash. Hence, in all likelihood our sample is excluding firms with the most negative values of ρ in their respective industries.

5.2 Alternative cash flow measures

Our estimates of cash flow parameters can be used for hypothesis testing with cross-sectional or panel data or for the numerical analysis, including simulation or calibration, of dynamic structural corporate finance models. But each application must be consistent with the definition of the operating cash flow variable used in the estimation.

As discussed in Section 1, measures of cash flow in the literature differ depending on whether the application intends to capture cash flow from operations, which is typically taken as given, or free cash flow available for savings and investment. Naturally, we can apply our filter to any definition as long as we interpret the parameters correctly in each

case.

Panel A of Table 9 reproduces our estimates using our benchmark measure: EBITDA minus the change in working capital. Panel B shows the importance of subtracting the second term. Without the adjustment, the average estimates of the short-term volatility, σ_A, and long-term volatility, σ_P, become smaller. Hence, cross-sectional differences in the working capital account, which is a necessary cash expense to sustain operations, contain useful information about short-term (and long-term) variability. Panel C shows the estimates for operating cash flows defined as EBITDA minus depreciation. The reason for subtracting depreciation is to consider the amount of depreciation as a committed expense to at least restore the capital stock each year. The estimates for σ_P, σ_A, and μ all have higher means and medians. The standard deviation is also substantially higher for the short- and long-term shocks, possibly due to heterogeneous practices to accrue depreciation.

5.3 Alternative firm grouping

We perform two additional exercises to assess the appropriateness of our method of grouping firms with similar cash flow dynamics. First, we re-estimate the cash flow model in equations (1)–(3) using all firms in each four-digit SIC industry classification and then test whether these parameter estimates can better explain cash holdings and equity issuance. The grouping at the four-digit SIC level is less granular and, as shown in Table 3, produces more heterogeneous groups of firms. We find that the cash flow model parameters estimated at the four-digit SIC level have similar distributions to those estimated more precisely using sorting by historical cash flow growth rates within three-digit SIC codes. However, the former do not explain the liquidity policies as well as the latter. While the regression coefficients have the predicted signs, their statistical and economic significance are markedly weaker.

Second, we conduct a placebo test and re-estimate the model parameters in (1)–(3) for each of ten thousand groups of ten firms selected at random and with replacement from our data set. Again, we test whether the cross-sectional variation in these estimates explains differences in cash holdings and equity issuance. In this case, the parameter estimates are

not related to corporate policies in any clear and systematic way.[20] We conclude that our grouping method captures the inherent similarities of the firms' cash flow dynamics, and the parameter estimates measure deep characteristics of firms' cash flow risk.

6 Conclusion

We estimate a canonical cash flow model that combines growth rate shocks, which have permanent effects, and short-term shocks, which cause temporary fluctuations. Efficient estimation of this model is achieved with a high level of granularity, under mild assumptions and using only cash flow data. As a result, estimates of the model's parameters provide a rich summary of a given firm's operating fundamentals via different combinations of productivity growth rates, exposure to permanent or short-term shocks and their correlation.

The estimated correlation between permanent and short-term shocks, a key parameter that summarizes a firm's hedging need, is a powerful indicator of within-industry differences risk taking. Together with the estimates of short-term and long-term shocks volatilities, they solve the propensity-to-save debate and explain corporate liquidity policies better than usual proxies. Our estimates can be used in future research to improve structural estimation or hypothesis testing of dynamic models.

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[20]We implement two different ways to merge randomly formed groups to Compustat firms. In one implementation, we match each Compustat firm to the parameter estimates of only one randomly selected group the firm is in. In another, we randomly select 918 of the 10,000 groups such that no firm belongs to more than one group. Neither implementation can reproduce the results under our proposed grouping.

Appendix

A. Kalman filter and maximum likelihood estimation

This section provides a detailed exposition of the model estimation approach used in Section 2. We first describe the state space model and then derive the Kalman filter to compute the likelihood of cash flow data.

A.1 The state space model

The state space model in (1)–(2) consists of a transition equation and a measurement equation. The transition equation describes the discrete-time dynamics of the latent state process, which is the unobserved asset productivity P_t. The measurement equation describes the relation between the state process and the observed cash flows of firms that share the same asset productivity. To facilitate the exposition, we use a standard notation in state space models, and present the model as if missing observations were absent (Appendix B.3 discusses how we handle missing observations).

Let X_t denote the asset productivity in year t, i.e., we set $X_t = P_t$. The transition equation (1) can be rewritten as

$$X_t = \Phi_X X_{t-1} + \omega_t \tag{A1}$$

where $\Phi_X = (1 + \mu)$, $\omega_t = \sigma_P X_{t-1} \varepsilon_t^P$ and $\varepsilon_t^P \sim \mathcal{N}(0,1)$. Thus, $\omega_t \sim \mathcal{N}(0, Q_t)$, where $Q_t = \sigma_P^2 X_{t-1}^2$, and the error term ε_t^P is the permanent shock to cash flows.

Let $Z_{i,t}$ denote the cash flows of firm i in year t, i.e., we set $Z_{i,t} = A_{i,t}$, and $Z_t = (Z_{1,t}, \ldots, Z_{N,t})'$ be the $N \times 1$ vector collecting the cash flows of the N firms that share the same asset productivity, where $'$ denotes transposition. The measurement equation in (2) can be written in vector form as

$$Z_t = H_Z X_t + u_t \tag{A2}$$

where the i-th element is $Z_{i,t} = X_t + u_{i,t}$, $u_{i,t} = \sigma_A X_{t-1} \varepsilon_{i,t}^A$, and $\varepsilon_{i,t}^A \sim \mathcal{N}(0,1)$ is the short-term shock to cash flows. In (A2), $H_Z = \mathbf{1}$, where $\mathbf{1} = (1, \ldots, 1)'$.

In classic applications of state space models, u_t is merely a measurement error of X_t, and it is assumed to be uncorrelated with X_t. In contrast, because permanent and short-term shocks in model (1)–(2) are correlated, u_t and X_t turn out to be correlated. Specifically, the correlation between $u_{i,t}$ and X_t is equal to ρ and enters the short-term shock $\varepsilon_{i,t}^A = \rho \varepsilon_t^P + \sqrt{1 - \rho^2} \varepsilon_{i,t}^T$, where $\varepsilon_{i,t}^T \sim \mathcal{N}(0,1)$ is the transitory shock, uncorrelated with ε_t^P. Thus,

$$Cov[X_t, u_{i,t}|X_{t-1}] = \mathbb{E}[\omega_t \, u_{i,t}|X_{t-1}] = \mathbb{E}[\sigma_P X_{t-1} \varepsilon_t^P \, \sigma_A X_{t-1} \varepsilon_{i,t}^A | X_{t-1}] = \rho \sigma_P \sigma_A X_{t-1}^2.$$

Collecting the transitory shocks of the N firms in $\varepsilon_t^T = (\varepsilon_{1,t}^T, \ldots, \varepsilon_{N,t}^T)'$, the error term $u_t = \sigma_A X_{t-1}(\rho \varepsilon_t^P \mathbf{1} + \sqrt{1 - \rho^2} \varepsilon_t^T) \sim \mathcal{N}(0, \Omega_t)$, where $\Omega_t = \sigma_A^2 X_{t-1}^2(\rho^2 \mathbf{1}\mathbf{1}' + (1 - \rho)^2 I_N)$, and I_N is the $N \times N$ identity matrix.

The correlation between u_t and X_t makes the standard Kalman filter biased and inconsistent. To overcome the issue posed by the correlation between u_t and X_t, we transform the measurement equation as follows

$$
\begin{aligned}
Z_t &= H_Z X_t + u_t + J(X_t - \Phi_X X_{t-1} - \omega_t) \\
&= (H_Z + J)X_t - J\Phi_X X_{t-1} + u_t - J\omega_t \\
&= H_Z^* X_t + \Phi_X^* X_{t-1} + u_t^*
\end{aligned}
\tag{A3}
$$

where $H_Z^* = H_Z + J$, $\Phi_X^* = -J\Phi_X$, $u_t^* = u_t - J\omega_t$, and J is a $N \times 1$ vector that will be defined shortly. In the first equation, the third term on the right hand side is zero by definition of the transition equation (A1). This means that the transformed measurement equation (A3) is an exact alternative representation of the measurement equation (A2). Importantly, the vector J is defined such that the transformed measurement error u_t^* is uncorrelated with X_t

$$
Cov[X_t, u_t^* | X_{t-1}] = \mathbb{E}[\omega_t u_t^* | X_{t-1}] = \mathbb{E}[\omega_t u_t | X_{t-1}] - J\mathbb{E}[\omega_t^2 | X_{t-1}] = 0.
\tag{A4}
$$

Solving the last equation for J gives $J = \mathbb{E}[\omega_t u_t | X_{t-1}]/\mathbb{E}[\omega_t^2 | X_{t-1}]$. In the state space model (A1)–(A2), J takes a simple form, that is $J = \rho\sigma_A/\sigma_P \mathbf{1}$.

Plugging J in u_t^* clarifies why u_t^* is uncorrelated with X_t in (A3)

$$
u_t^* = u_t - J\omega_t = \sigma_A X_{t-1}\varepsilon_t^A - \rho\frac{\sigma_A}{\sigma_P}\mathbf{1}\sigma_P X_{t-1}\varepsilon_t^P = \sigma_A X_{t-1}(\varepsilon_t^A - \rho\mathbf{1}\varepsilon_t^P) = \sigma_A X_{t-1}\sqrt{1-\rho^2}\varepsilon_t^T
$$

where ε_t^T is by definition uncorrelated with X_t, and we used $\varepsilon_t^A = (\varepsilon_{1,t}^A, \ldots, \varepsilon_{N,t}^A)'$. The error term u_t^* is by definition uncorrelated with X_{t-1} too.

The transformation of the measurement equation in (A3) can be applied to more general state space models to handle the correlation between state variables and measurement errors. For example, if X_t is a $k \times 1$ state variable, then $J = \mathbb{E}[u_t \omega_t' | X_{t-1}] \mathbb{E}[\omega_t \omega_t' | X_{t-1}]^{-1}$, which is an $N \times k$ matrix. Also, J could be time varying when the conditional expectations above are state dependent.

In the signal processing literature, Ma, Wang, and Chen (2010) suggest to transform the transition equation to account for the correlation between measurement and transition errors in state space models. We use a different approach and transform the measurement equation which results in a stable Kalman filter for the state space model in (1)–(2).

A.2 The generalized Kalman filter

Because the transformed measurement equation (A3) features X_{t-1} in the right hand side, it is necessary to re-derive the Kalman filter to filter out the latent state process.

Let $\hat{X}_{t|t-1} = \mathbb{E}_{t-1}[X_t]$ and $\hat{Z}_{t|t-1} = \mathbb{E}_{t-1}[Z_t]$ denote the expectation of X_t and Z_t, respectively, using information up to and including time $t-1$, and let $V_{t|t-1}$ and $F_{t|t-1}$ denote the corresponding (a priori) error variance and error covariance matrix. Furthermore, let $\hat{X}_t = \mathbb{E}_t[X_t]$ denote the expectation of X_t including information at time t, and let V_t denote the (a posteriori) error variance.

The Kalman filter consists of two steps, i.e., prediction and update. In the prediction step, $\hat{X}_{t|t-1}$ and $V_{t|t-1}$ are given by

$$
\begin{align}
\hat{X}_{t|t-1} &= \Phi_X \hat{X}_{t-1} \tag{A5}\\
V_{t|t-1} &= \Phi_X V_{t-1} \Phi_X + Q_t. \tag{A6}
\end{align}
$$

and $\hat{Z}_{t|t-1}$ and $F_{t|t-1}$ are in turn given by

$$
\begin{align}
\hat{Z}_{t|t-1} &= H_Z \hat{X}_{t|t-1} + \Phi_X^* \hat{X}_{t-1} \tag{A7}\\
F_{t|t-1} &= H_Z^* V_{t|t-1} H_Z^{*\prime} + \Phi_X^* V_{t-1} \Phi_X^{*\prime} + \Omega_t^*. \tag{A8}
\end{align}
$$

Because the transition equation (A1) is standard, $\hat{X}_{t|t-1}$ and $V_{t|t-1}$ take the usual forms in Kalman filtering. The transformed measurement equation (A3) changes $\hat{Z}_{t|t-1}$ and $F_{t|t-1}$ relative to standard Kalman filtering, with the additional terms in Φ_X^*.

In the update step, the estimate of the state process X_t is refined based on the difference between the observed and predicted values of Z_t, with $\hat{X}_t$ and V_t given by

$$
\begin{align}
\hat{X}_t &= \hat{X}_{t|t-1} + G_t'(Z_t - \hat{Z}_{t|t-1}) \tag{A9}\\
V_t &= V_{t|t-1} - 2V_{t|t-1} H_Z^{*\prime} G_t + G_t' F_{t|t-1} G_t \tag{A10}
\end{align}
$$

where G_t is an $N \times 1$ vector called Kalman gain, which is determined by minimizing V_t with respect to G_t. Solving the first order condition $\partial V_t/\partial G_t' = 0$ for G_t, gives $G_t' = V_{t|t-1} H_Z^{*\prime} F_{t|t-1}^{-1}$. This choice of G_t minimizes V_t because $\partial^2 V_t/(\partial G_t \, \partial G_t') = 2F_{t|t-1}$ is positive definite.

Model estimation is achieved by maximizing the log-likelihood of cash flows data of N firms over T periods with respect to the model parameters μ, σ_P, σ_A, and ρ. Specifically, for fixed model parameters the generalized Kalman filter (A5)–(A10) is run to compute the log-likelihood

$$
\sum_{t=1}^{T} -\frac{1}{2} \left[N \log(2\pi) + \log |F_{t|t-1}| + (Z_t - \hat{Z}_{t|t-1})' F_{t|t-1}^{-1} (Z_t - \hat{Z}_{t|t-1}) \right]. \tag{A11}
$$

Model parameters are changed as to increase the value of the log-likelihood, which then requires to re-run the generalized Kalman filter, and re-compute the log-likelihood.[21] The iterative procedure is repeated until convergence of the numerical likelihood search. As mentioned in Section 2.2, on a common laptop computer, it takes less than one second to fit the model to a panel of 10 firm cash flows observed over 46 years.

A.3 Missing observations handled with Kalman filtering

A prominent feature of cash flow data are missing observations. In our panel, 56% of firm-year observations are missing relative to the full balanced panel. Although our Kalman filter

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[21]The starting value of the state process X is set equal to the average of cash flows at $t = 1$, but is then optimized during the likelihood search.

is different from the standard one, missing values can be handled using the usual method in Kalman filtering; see Section 3 in Shumway and Stoffer (1982). For completeness we briefly recall the procedure.

Suppose that there are no missing observations in year t. Then, the measurement equation (A3) holds. That is, Z_t collects the cash flows of all the N firms in a year t. Suppose now that the cash flow data of some firms in year t are missing. The idea is to "select" the components of Z_t corresponding to firms with observed (not missing) cash flow data. This task is achieved by simply using a matrix S_t consisting of zeros and ones with dimension $M_t \times N$, where M_t is the number of firms with observed cash flow data. To illustrate, consider an extreme and unrealistic case in which only the cash flow of the first firm in Z_t is available in year t. In that case, $S_t = (1, 0, \ldots, 0)$ is a $1 \times N$ row vector, $M_t = 1$ and $S_t Z_t$ is the cash flow of that firm. If cash flows of all N firms are available in year t, then S_t is a $N \times N$ identity matrix.

The procedure to compute the log-likelihood with missing observations is as follows. First, for each year t, construct the matrix S_t based on the position of observed cash flows in Z_t. Then, pre-multiply both sides of the measurement equation (A3) by S_t and use this measurement equation to run the generalized Kalman filter. Finally, compute the log-likelihood in (A11) replacing N by M_t.

The matrix S_t is time dependent and needs to be computed for each year t. This time dependence allows the procedure to accommodate missing observations in different positions of the cash flow panel as well as entry and exit of firms in the panel.

A.4 Identification of shock correlation

To illustrate the issue of the identification of shock correlation, we use a popular model in the corporate finance literature. The model features persistent and short-term productivity shocks at a firm level. Denote $y_{i,t}$ an observable productivity or cash flow process for a given firm i,

$$y_{i,t} = \varepsilon_{i,t} + \sigma_\nu \nu_{i,t} \tag{A12}$$

where $\varepsilon_{i,t}$ is an AR(1) process, namely $\varepsilon_{i,t} = \beta \varepsilon_{i,t-1} + \sigma_\eta \eta_{i,t}$ and $0 < \beta < 1$ and $\sigma_\eta > 0$. The process $\eta_{i,t} \sim i.i.d.\mathcal{N}(0,1)$ models persistent (or often called long-term) shocks. The process $\nu_{i,t} \sim i.i.d.\mathcal{N}(0,1)$ models short-term shocks and $\sigma_\nu > 0$. Both shocks are firm-specific. The usual assumption in the literature is that these shocks are uncorrelated. We consider instead the case in which these shocks are correlated, $corr[\eta_{i,t}, \nu_{i,t}] = \rho$. It is perhaps surprising that even observing an infinite time series of $y_{i,t}$, the correlation ρ (and other model parameters) cannot be identified. Below we formally prove this result.

A time series model is identified when the system of equations, matching population and model-based autocovariances, can be solved uniquely for the model parameters. The unknowns in this system are the model parameters. Population autocovariances are (asymptotically) known. Define the autocovariance function as $\gamma(h) = Cov[y_{i,t}, y_{i,t-h}]$, for $h = 0, 1, \ldots,$

then

$$\gamma(0) = \frac{\sigma_\eta^2}{1 - \beta^2} + \sigma_\nu^2 + 2\rho\sigma_\eta\sigma_\nu \tag{A13}$$

$$\gamma(h) = \beta^h \left[\frac{\sigma_\eta^2}{1 - \beta^2} + \rho\sigma_\eta\sigma_\nu \right]. \tag{A14}$$

The parameter β can be easily identified from the decay of the autocovariance function $\gamma(h)$, say from the equation $\gamma(h_2)/\gamma(h_1) = \beta^{h_2-h_1}$ for $h_2 > h_1 \geq 1$, and it is therefore taken as known in the discussion below. Although there is an infinite number of equations (A14) for $h \geq 1$, effectively, (A13)–(A14) is a system of two equations in three unknowns, $\rho, \sigma_\eta, \sigma_\nu$, and the model in (A12) is not identified.

To see the lack of identification of the shock correlation, suppose for simplicity that $\rho > 0$. Solving (A13) for σ_ν (which then admits only one real and positive solution) and plugging this solution in (A14) gives

$$\gamma(h) = \beta^h \left[\frac{\sigma_\eta^2}{1 - \beta^2} + \rho\sigma_\eta \left(\sqrt{\rho^2\sigma_\eta^2 + \left(\gamma(0) - \frac{\sigma_\eta^2}{1 - \beta^2}\right)} - \rho\sigma_\eta \right) \right]$$

which is effectively one equation in two unknowns, ρ and σ_η. Therefore, ρ and σ_η are not identified.

Consider now the model

$$y_{i,t} = \varepsilon_t + \sigma_\nu \nu_{i,t} \tag{A15}$$

in which the persistent shock $\varepsilon_t = \beta\varepsilon_{t-1} + \sigma_\eta\eta_t$ is not firm-specific but common across firms, and is still correlated with the short-term shock, $corr[\eta_t, \nu_{i,t}] = \rho$. The persistent shock ε_t plays the role of a "systemic factor" for the firms' productivity. The short-term shock can be decomposed as $\nu_{i,t} = \rho\varepsilon_t + \sqrt{1 - \rho^2}\nu_{i,t}^T$, where $\nu_{i,t}^T$ is the firm-specific transitory shock, uncorrelated with ε_t. The cross-sectional mean, $\overline{y}_t$, is such that

$$\overline{y}_t = \frac{1}{N} \sum_{i=1}^N y_{i,t} = \frac{1}{N} \sum_{i=1}^N (\varepsilon_t + \sigma_\nu\nu_{i,t}) = \frac{1}{N} \sum_{i=1}^N (\varepsilon_t + \sigma_\nu(\rho\varepsilon_t + \sqrt{1 - \rho^2}\nu_{i,t}^T))$$

and therefore when $N \to \infty$, $\overline{y}_t = \varepsilon_t(1 + \rho\sigma_\nu)$. The last equation indicates that if, for example, $\rho > 0$, then firms' productivity load more on the systemic factor ε_t relative to the case when $\rho = 0$. Importantly, the autocovariances of $\overline{y}_t$ provide additional moment conditions to identify the model in (A15). In essence, additional information from the cross-section of firms allows to identify the model and in particular the shock correlation. Denote $\overline{\gamma}(0) = V[\overline{y}_t]$, then

$$\overline{\gamma}(0) = \frac{\sigma_\eta^2}{1 - \beta^2}(1 + \rho\sigma_\nu)^2. \tag{A16}$$

The moment conditions (A13), (A14) and (A16) provide a system of three equations in three unknowns, $\rho, \sigma_\eta, \sigma_\nu$, to identify the model in (A15). This system can be solved as follows. Solving (A14) with respect to $\rho\sigma_\nu$ and plugging this solution in (A16) gives a quadratic equation in which σ_η is the only unknown. Ensuring that only one real and positive solution exists, identifies σ_η. The difference between (A13) and (A14) gives

$$\gamma(0) - \frac{\gamma(h)}{\beta^h} = \sigma_\nu^2 + \rho\sigma_\eta\sigma_\nu. \tag{A17}$$

Matching the expression of $\rho\sigma_\eta\sigma_\nu$ from (A17) and from (A14) gives a linear equation in which σ_ν^2 is the only unknown, identifying this parameter. Having identified σ_η and σ_ν, (A13) can be used to identify ρ.

In sum, a model in which persistent and short-term shocks are both firm-specific is not identified. Instead, assuming that persistent shocks are common across firms allows to identify the shock correlation, because these common shocks would behave like a systemic factor for firms' productivity.

B. Monte Carlo analysis of estimation accuracy

To check the accuracy of our estimation method, we conduct a Monte Carlo simulation. In the cash flow model given by equations (1) and (3), we set the parameters ρ, σ_A, σ_P, and μ to their respective average estimated values as in Table 4. We then use the model to simulate 10,000 panels of cash flows. As in our empirical analysis with Compustat data, each simulated panel consists of the cash flows of 10 firms over 48 years. For each simulated panel we estimate the model in (1)–(3) using maximum likelihood with our generalized Kalman filter, as described in Appendix A.2. As a benchmark method, we also estimate the cash flow model using maximum likelihood with a standard Kalman filter.

The standard filter presumes that the correlation between permanent and short-term cash flow shocks is zero, and thus delivers no estimate of ρ. As a measure of estimation accuracy, for each estimated parameter $\hat{\theta} = \{\hat{\rho}, \hat{\sigma}_A, \hat{\sigma}_P, \hat{\mu}\}$, we compute the mean square error (MSE), i.e., $\sum_{j=1}^{10000}(\hat{\theta}_j - \theta_0)^2/10000$, where $\hat{\theta}_j$ is the estimate of the parameter θ based on the j-th simulated panel of cash flows and θ_0 is the true parameter value. To compare MSE's across parameters, we report the relative MSE, i.e., the MSE divided by the absolute value of θ_0.

Underscoring the accuracy of our estimation method, the MSE's of the maximum likelihood estimates of the parameters μ, σ_P and σ_A with the generalized Kalman filter are, respectively, 0.360, 0.085 and 0.106. The MSE's of the maximum likelihood estimation with the standard Kalman filter are an order of magnitude larger than those with the generalized Kalman filter. The ratios between the two MSE's are 2.2, 1.7 and 2.1, respectively. Hence, our method is uniformly more accurate than maximum likelihood with a standard Kalman filter, often by a large extent. Finally, the MSE of ρ based on maximum likelihood with the generalized Kalman filter is 0.034, which is even smaller than the MSE's of the other parameters. As mentioned above, maximum likelihood with standard Kalman filter provides no estimate of ρ.

In sum, the Monte Carlo simulation above shows that maximum likelihood with the generalized Kalman filter delivers accurate estimates of the cash flow model in equations (1) and (3) while outperforming the maximum likelihood estimator with a standard Kalman filter. The latter method is not suited to handle the correlation between permanent and short-term shocks in (1)–(3).

C. Asset growth volatilities

This exercise illustrates a numerical application of our decomposition. The purpose is twofold. First, and as a validation of our results, we ask whether the parameter estimates in Table 4 imply asset volatilities that are comparable to those of actual Compustat firms. It is not clear this should be the case: our estimator recovers cash flow parameters from cash flow data only, and does not impose the restrictions from corporate policies that feed from those parameters to predict asset values and volatilities.

Second, we also test whether our implied asset volatilities are robust, in the sense that they are not driven by the financing model assumptions but instead by inference based only on cash flow data, using the model in (1)–(2). As noted by Gorbenko and Strebulaev (2010), an important limitation of standard EBIT models with only permanent shocks (e.g., Leland (1994)) is that asset growth volatilities are equal to cash flow volatilities. Hence, this exercise evaluates the extent to which the cash flow structure with permanent and transitory shocks helps reconcile the large differences between relatively high cash flow volatilities and the much more moderate asset volatilities in the data.

C.1 Cash flow model

To compute the model-implied asset volatilities, we employ a version of the model of Décamps et al. (2017). In this continuous time model , operating revenue is subject to permanent and transitory shocks. Asset productivity $P = (P_t)_{t \geq 0}$ is governed by the geometric Brownian motion:

$$dP_t = \mu P_t dt + \sigma_P P_t dW_t^P \tag{A18}$$

where μ and $\sigma_P > 0$ are constant and $W^P = (W_t^P)_{t \geq 0}$ is a standard Brownian motion. Therefore, asset productivity is non-stationary and features permanent shocks. In addition to these shocks, cash flows are subject to short-term shocks. For a given firm, the cash flows dA_t are proportional to P_t but uncertain and governed by:

$$dA_t = P_t dt + \sigma_A P_t dW_t^A \tag{A19}$$

where $\sigma_A > 0$ is constant and $W^A = (W_t^A)_{t \geq 0}$ is a standard Brownian motion. W^A and W^P can be correlated with correlation coefficient ρ, in that

$$\mathbb{E}[dW_t^P dW_t^A] = \rho dt, \text{ with } \rho \in (-1, 1). \tag{A20}$$

The specification for cash flow dynamics in equations (A18) and (A19) nests those in traditional dynamic corporate finance models. If $\sigma_A = 0$, we obtain the model with time-varying profitability applied extensively in dynamic capital structure models (see Goldstein, Ju, and Leland (2001), Strebulaev (2007), or Morellec, Nikolov, and Schürhoff (2012)) and real-options models (see Abel and Eberly (1994), Carlson, Fisher, and Giammarino (2006), or Morellec and Schürhoff (2011)). If $\mu = \sigma_P = 0$, we obtain the stationary framework of dynamic agency models (see DeMarzo and Sannikov (2006) or DeMarzo, Fishman, He, and Wang (2012)) and liquidity management models (see Décamps, Mariotti, Rochet, and Villeneuve (2011), Bolton, Chen, and Wang (2011), or Hugonnier, Malamud, and Morellec (2015)).

The transition equation (1) is a simple Euler discretization of (A18). The measurement equation (2) is related to an Euler discretization of (A19) and it is obtained by setting $A_{i,t}$ equal to the cash flow accumulated over year t, for firm i. In (2), P_{t-1} and not P_t enters the error term $P_{t-1}\sigma_A\varepsilon_{i,t}^A$ for it to have zero mean.

With the above specification, the firm's cash flow over the time interval $[t, t+dt]$ is given by

$$dA_t = P_t dt + \sigma_A P_t(\rho dW_t^P + \sqrt{1-\rho^2} dW_t^T) \tag{A21}$$

where $W^T = (W_t^T)_{t \geq 0}$ is a Brownian motion independent from W^P. This decomposition implies that short-term cash flow shocks dW_t^A consist of transitory shocks dW_t^T and permanent shocks dW_t^P.

C.2 Management's optimization problem

Short-term shocks expose the firm to potential losses that can be covered using cash reserves or new equity financing. Specifically, management is allowed to retain earnings inside the firm and we denote by M_t the firm's cash holdings at any time $t > 0$. Cash reserves earn a rate of return $r - \lambda$ inside the firm, where $\lambda > 0$ is a cost of holding liquidity. The firm can also raise additional funds from investors. External equity financing is costly with a fixed cost ϕP_t and a proportional cost θ. The dynamics of cash reserves are then given by:

$$dM_t = (r - \lambda)M_t dt + \left(dt + \sigma_A \rho dW_t^P + \sqrt{1-\rho^2} dW_t^T\right) P_t + \frac{dE_t}{\theta} - d\Phi_t - dL_t \tag{A22}$$

where E_t, Φ_t, and L_t are non-decreasing processes that represents the cumulative gross external financing, the cumulative fixed cost of financing, and the cumulative dividend paid to shareholders. Equation (A22) is an accounting identity that shows that cash reserves increase with the interest earned on cash holdings (first term on the right hand side), with the firm's earnings (second term), and with net external equity (third and fourth terms) and decrease with payouts (last term).

Management chooses the cash savings/payout and equity financing policies to maximize shareholder value. There are two state variables for the firm's optimization problem: Prof-

itability P_t and the cash balance M_t. We can thus write this problem as

$$V(p, m) = \sup_{L,E} \mathbb{E}_{p,m} \left[\int_0^\infty e^{-rt}(dL_t - dE_t) \right] \tag{A23}$$

where p and m denote realizations of P and M at time $t = 0$.

C.3 Implied volatilities

To compute the model-implied asset volatilities, we use the cash flow process estimated above and solve for optimal financing and liquidity policies and firm value. We thus quantitatively link the cash flow parameters (μ, σ_A, σ_P, and ρ) to asset volatility.

We calculate asset volatilities at the group level, consistently with the level of granularity of the estimation of cash flow parameters. The empirical asset volatilities are estimated as weighted averages of equity and debt volatilities following the approach in Bharath and Shumway (2008) using daily stock returns. Model-implied volatilities are averages of all firm level volatilities within a group using the estimated cash flow parameters reported in Table 4 for each group of firms. We drop groups of firms with insufficient stock price data or where the model cannot be solved given parameter values, winsorizing actual and predicted asset volatilities at the 5th and 95th percentiles.[22]

<div style="text-align:center">

Insert Table 10 Here

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Table 10 presents a comparison of the empirical and model-implied asset volatilities. The average and median empirical asset volatilities are 0.476 and 0.447, respectively. In the baseline case, the model-implied volatilities are sightly higher, at 0.559 and 0.495 respectively, but very close to the empirical ones. It is remarkable that model-implied asset volatilities appear to match actual asset volatilities that were not used during the estimation process. While similar at the center of the distribution, the model-implied volatilities tend to be somewhat more extreme in the tails compared to the empirical ones. This suggests that there could be some forces beyond those in the Décamps et al. (2017) model moderating the volatility of real firms' asset values. Additional rows for model-implied distributions in Table 10 present calculations based on departures from the baseline parameters. The results show that the similarity between the empirical and model-implied distributions is robust and driven by the estimates of the parameters of the cash flow dynamics rather than the assumed values for the remaining parameters.

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[22]The remaining model parameters follow the choices in Décamps et al. (2017) and in Bolton et al. (2013): the risk-free rate $r = 0.08$, the carry cost of cash $\lambda = 0.02$, proportional equity issuance cost $p = 1.06$, fixed equity issuance cost $\Phi = 0.002$, the market price of risk of temporary and permanent shocks $\eta^T = \eta^P = 0.4$, and the correlation of temporary and permanent shocks with market shocks $\xi^T = \xi^P = 0.4$; cash holdings are assumed at the target level.

References

Abel, A., and J. Eberly. 1994. A unified model of investment under uncertainty. *American Economic Review* 84:1369–1384.

Abel, A., and J. Eberly. 2011. How Q and cash flow affect investment without frictions: An analytic explanation. *Review Economic Studies* 78:1179–1200.

Acharya, V., H. Almeida, and M. Campello. 2007. Is cash negative debt? A hedging perspective on corporate financial policies. *Journal of Financial Intermediation* 16:515–554.

Almeida, H., M. Campello, and M. Weisbach. 2004. The cash flow sensitivity of cash. *Journal of Finance* 59:1777–1804.

Bansal, R., R. Dittmar, and D. Kiku. 2008. Cointegration and consumption risks in asset returns. *Review of Financial Studies* 22:1343–1375.

Bates, T., K. Kahle, and R. Stulz. 2009. Why do U.S. firms hold so much more cash than they used to? *Journal of Finance* 64:1985–2021.

Berk, J., and P. DeMarzo. 2019. *Corporate Finance 5th edition*. Pearson.

Bharath, S., and T. Shumway. 2008. Forecasting default with the Merton distance-to-default model. *Review of Financial Studies* 21:1339–1369.

Blundell, R., L. Pistaferri, and I. Preston. 2008. Consumption inequality and partial insurance. *American Economic Review* 98:1887–1921.

Boehmer, E., and J. Wu. 2013. Short selling and the price discovery process. *Review of Financial Studies* 26:287–322.

Bolton, P., H. Chen, and N. Wang. 2011. A unified theory of Tobin's Q, corporate investment, financing, and risk management. *Journal of Finance* 66:1545–1578.

Bolton, P., H. Chen, and N. Wang. 2013. Market timing, investment, and risk management. *Journal of Financial Economics* 109:40–62.

Bolton, P., N. Wang, and J. Yang. 2019. Optimal Contracting, Corporate Finance, and Valuation with Inalienable Human Capital. *Journal of Finance* 74:1363–1429.

Bolton, P., N. Wang, and J. Yang. 2020. Leverage Dynamics and Financial Flexibility. Working paper, Columbia University.

Brennan, M., and A. Subrahmanyam. 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics* 41:441–464.

Breugem, M., R. Marfe, and F. Zucchi. 2020. Corporate Policies and the Term Structure of Risks. Working paper, Collegio Carlo Alberto.

Byun, S., V. Polkovnichenko, and M. Rebello. 2019. Composition of cash flow shocks and debt financing. Working paper, University of Texas.

Carlson, M., A. Fisher, and R. Giammarino. 2004. Corporate investment and asset price dynamics: Implications for the cross-section of returns. *Journal of Finance* 59:2577–2603.

Carlson, M., A. Fisher, and R. Giammarino. 2006. Corporate investment and asset price dynamics: Implications for SEO event-studies and long-run performance. *Journal of Finance* 61:1009–1034.

Chang, X., S. Dasgupta, G. Wong, and J. Yao. 2014. Cash-flow sensitivities and the allocation of internal cash flow. *Review of Financial Studies* 27:3628–3657.

Cocco, J., F. Gomes, and P. Maenhout. 2005. Consumption and portfolio choice over the life cycle. *Review of Financial Studies* 18:491–533.

Cochrane, J. 1994. Permanent and transitory components of GNP and stock prices. *Quarterly Journal of Economics* 109:241–265.

Cohen, R., P. Gompers, and T. Vuolteenaho. 2002. Who underreacts to cash-flow news? Evidence from trading between individuals and institutions. *Journal of Financial Economics* 66:409–462.

Danis, A., D. Rettl, and T. Whited. 2012. Refinancing, profitability, and capital structure. *Journal of Financial Economics* 114:424–443.

De Loecker, J., J. Eeckhout, and G. Unger. 2018. The rise of market power and the macroeconomic implications. NBER working paper.

Décamps, J.-P., S. Gryglewicz, E. Morellec, and S. Villeneuve. 2017. Corporate policies with permanent and transitory shocks. *Review of Financial Studies* 30:162–210.

Décamps, J.-P., T. Mariotti, J.-C. Rochet, and S. Villeneuve. 2011. Free cash flow, issuance costs, and stock prices. *Journal of Finance* 66:1501–1544.

DeMarzo, P., M. Fishman, Z. He, and N. Wang. 2012. Dynamic agency and the q theory of investment. *Journal of Finance* 67:2295–2340.

DeMarzo, P., and Y. Sannikov. 2006. Optimal security design and dynamic capital structure in a continuous-time agency model. *Journal of Finance* 61:2681–2724.

Denis, D., and V. Sibilkov. 2010. Financial constraints, investment, and the value of cash holdings. *Review of Financial Studies* 23:247–269.

Duchin, R. 2010. Cash holdings and corporate diversification. *Journal of Finance* 65:955–992.

Eckbo, E., and M. Kisser. 2020. The leverage-profitability puzzle resurrected. *Review of Finance* Forthcoming.

Erickson, T., C. Jiang, and T. Whited. 2014. Minimum distance estimation of the error-in-variables model using linear cumulant equations. *Journal of Econometrics* 183:211–221.

Fama, E. F., and K. R. French. 1997. Industry costs of equity. *Journal of Financial Economics* 43:153–193.

Froot, K., D. Scharfstein, and J. Stein. 1993. Risk Management: Coordinating Corporate Investment and Financing Policies. *Journal of Finance* 48:1629–1658.

Garleanu, N., L. Kogan, and S. Panageas. 2012a. Displacement risk and asset returns. *Journal of Financial Economics* 105:491–510.

Garleanu, N., S. Panageas, and J. Yu. 2012b. Technological growth and asset pricing. *Journal of Finance* 67:1265–1292.

Glosten, L., and L. Harris. 1988. Estimating the components of the bid/ask spread. *Journal of Financial Economics* 21:123–142.

Goldstein, R., N. Ju, and H. Leland. 2001. An EBIT-based model of dynamic capital structure. *Journal of Business* 74:483–512.

Gorbenko, A. S., and I. A. Strebulaev. 2010. Temporary versus permanent shocks: Explaining corporate financial policies. *Review of Financial Studies* 23:2591–2647.

Gottschalk, P., and R. Moffitt. 2009. The rising instability of U.S. earnings. *Journal of Economic Perspectives* 23:3–24.

Graham, J., and M. Leary. 2018. The evolution of corporate cash. *Review of Financial Studies* 31:4288–4333.

Gryglewicz, S., S. Mayer, and E. Morellec. 2020. Agency conflicts and short- vs. long-termism in corporate policies. *Journal of Financial Economics* 136:718–742.

Guay, W., and J. Harford. 2000. The cash-flow permanence and information content of dividend increases versus repurchases. *Journal of Financial Economics* 57:385–415.

Guiso, L., L. Pistaferri, and F. Schivardi. 2005. Insurance within the firm. *Journal of Political Economy* 113:1054–1087.

Hackbarth, D., A. Rivera, and T.-Y. Wong. 2020. Optimal short-termism. Working paper, Boston University.

Hamilton, J. 1994. *Time series analysis*. Princeton, NJ: Princeton University Press.

Hamilton, J. 2018. Why you should never use the Hodrick-Prescott filter. *Review of Economics and Statistics* 100:831–843.

He, Z. 2009. Optimal executive compensation when firm size follows a geometric brownian motion. *Review of Financial Studies* 22:859–892.

Hennessy, C., and T. Whited. 2007. How costly is external financing? Evidence from a structural estimation. *Journal of Finance* 62:1705–1745.

Hoffmann, F., and S. Pfeil. 2010. Reward for luck in a dynamic agency model. *Review of Financial Studies* 23:3329–3345.

Hugonnier, J., S. Malamud, and E. Morellec. 2015. Capital supply uncertainty, cash holdings, and investment. *Review of Financial Studies* 28:391–445.

Kim, W., and M. Weisbach. 2008. Motivations for public equity offers: An international perspective. *Journal of Financial Economics* 87:281–307.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman. 2017. Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics* 132:665–712.

Kwiatkowski, D., P. Phillips, P. Schmidt, and Y. Shin. 1992. Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics* 54:159–178.

Lee, B.-S., and O. M. Rui. 2007. Time-series behavior of share repurchases and dividends. *Journal of Financial and Quantitative Analysis* 42:119–142.

Leland, H. E. 1994. Corporate debt value, bond covenants, and agency costs. *Journal of Finance* 49:1213–1252.

Leland, H. E. 1998. Agency costs, risk management, and capital structure. *Journal of Finance* 53:1213–1243.

Ma, L., H. Wang, and J. Chen. 2010. Analysis of Kalman filter with correlated noises under different dependence. *Journal of Information and Computational Science* 5:1147–1154.

McLean, D. 2011. Share issuance and cash savings. *Journal of Financial Economics* 99:693–715.

Meghir, C., and L. Pistaferri. 2004. Income variance dynamics and heterogeneity. *Econometrica* 72:1–32.

Morellec, E., B. Nikolov, and N. Schürhoff. 2012. Corporate governance and capital structure dynamics. *Journal of Finance* 67:803–848.

Morellec, E., and N. Schürhoff. 2011. Corporate investment and financing under asymmetric information. *Journal of Financial Economics* 99:262–288.

Morellec, E., and C. Smith. 2007. Agency conflicts and risk management. *Review of Finance* 11:1–23.

Opler, T., L. Pinkowitz, R. Stulz, and R. Williamson. 1999. The determinants and implications of corporate cash holdings. *Journal of Financial Economics* 52:3–46.

Rebelo, S., N. Wang, and J. Yang. 2020. Rare disasters, financial development, and sovereign debt. Working paper, Northwestern University.

Riddick, L., and T. Whited. 2009. The corporate propensity to save. *Journal of Finance* 64:1729–1766.

Shumway, R., and D. Stoffer. 1982. An approach to time series smoothing and forecasting using the EM algorithm. *Journal of Time Series Analysis* 3:253–264.

Strebulaev, I. A. 2007. Do tests of capital structure theory mean what they say? *Journal of Finance* 62:1747–1787.
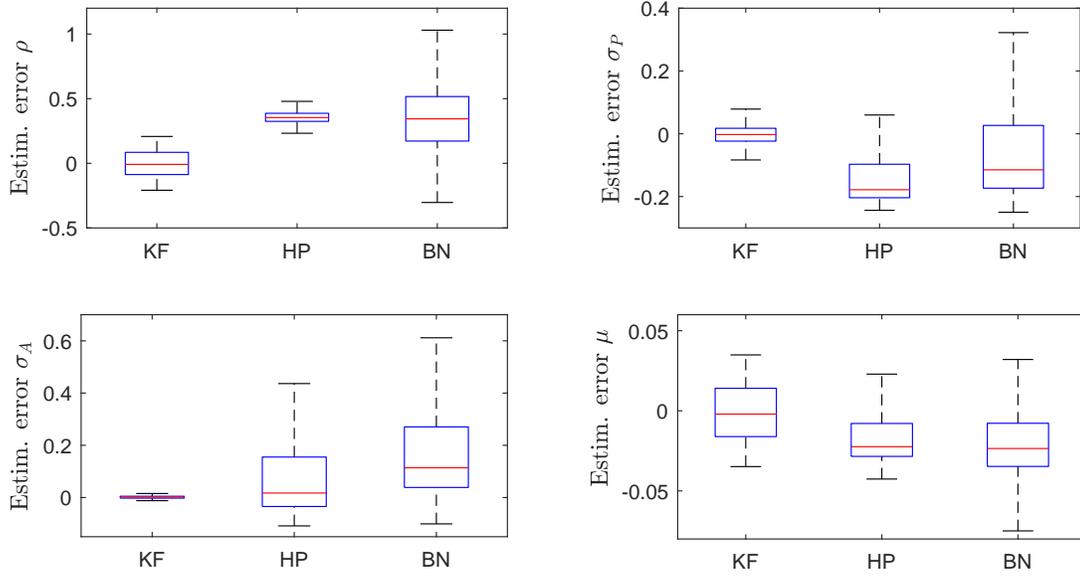
Figure 1: Estimation errors of cash flow shocks in simulated data. The model in (1)–(3) with parameter values $\rho = -0.21$, $\sigma_P = 0.25$, $\sigma_A = 0.12$, $\mu = 0.01$ is used to simulate 1,000 panels of cash flows for 10 firms over 50 years. The box plots show the estimation errors of the permanent and short-term shock correlation, ρ, the volatility of permanent and transitory shocks, σ_P and σ_A, and the drift of the permanent process μ. Cash flow shocks are recovered using the Kalman filter (KF), the Hodrick–Prescott filter (HP) and the Beveridge–Nelson decomposition (BN).
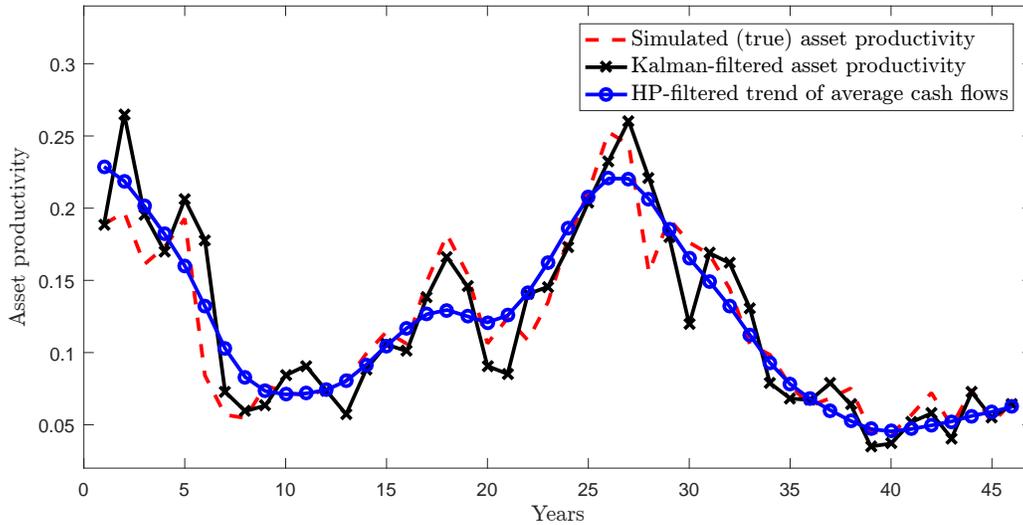
Figure 2: Generalized Kalman filter and Hodrick–Prescott filter applied to simulated cash flow data. Based on a panel of simulated cash flows from model in (1)–(3), the graph shows the time series trajectory of the true latent asset productivity, the Kalman-filtered asset productivity, and the trend component of the group average of cash flows from the HP filter. The Kalman-filtered asset productivity tracks closely the true asset productivity, while the HP filter, being a cubic spline smoother, provides a too smooth approximation of the asset productivity.
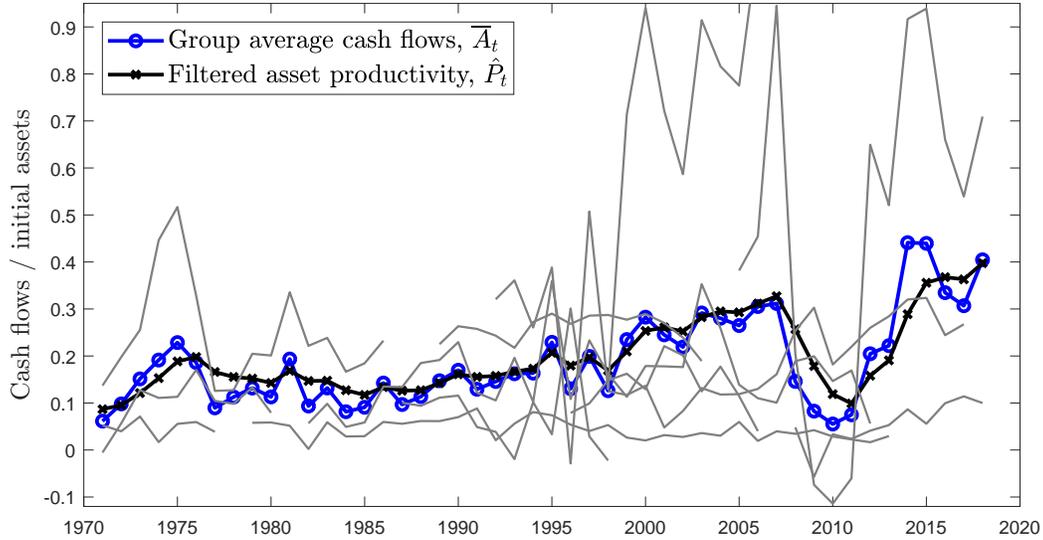
Figure 3: Cash flows for one group of firms. This figure shows the yearly firm cash flows scaled by the initial level of assets for a select group of ten firms in the 100 three-digit SIC code.
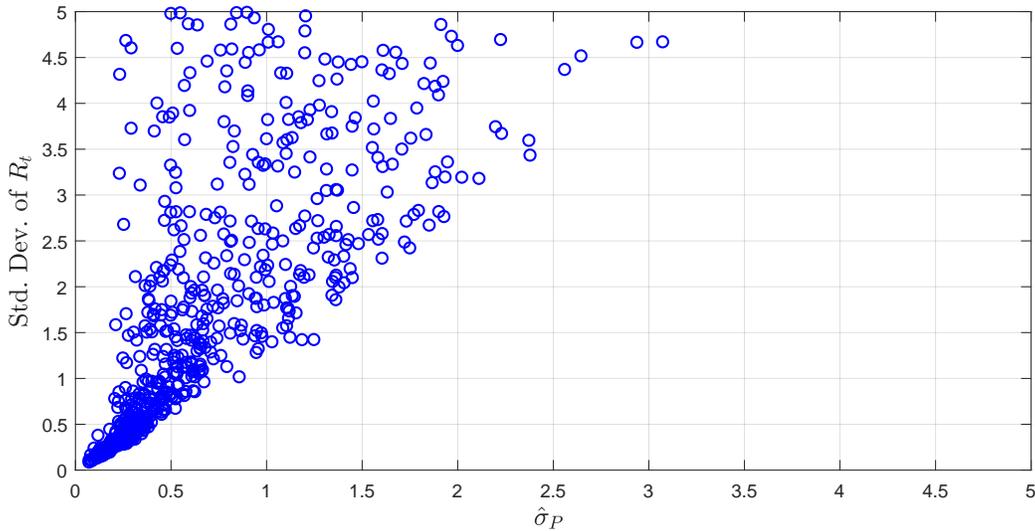
Figure 4: Scatter plot of permanent shock volatilities. The x-axis reports the model-based estimated volatilities of permanent shocks, σ_P in the model in (1)–(3), for each group of firms in our sample. The y-axis reports the observed time series standard deviations of R_t in (8) for $t = 1, \ldots, T$, i.e., the relative change of group-specific average cash flows. The sample data covers 10,136 firms, from 1971 to 2018, sorted in 918 groups.
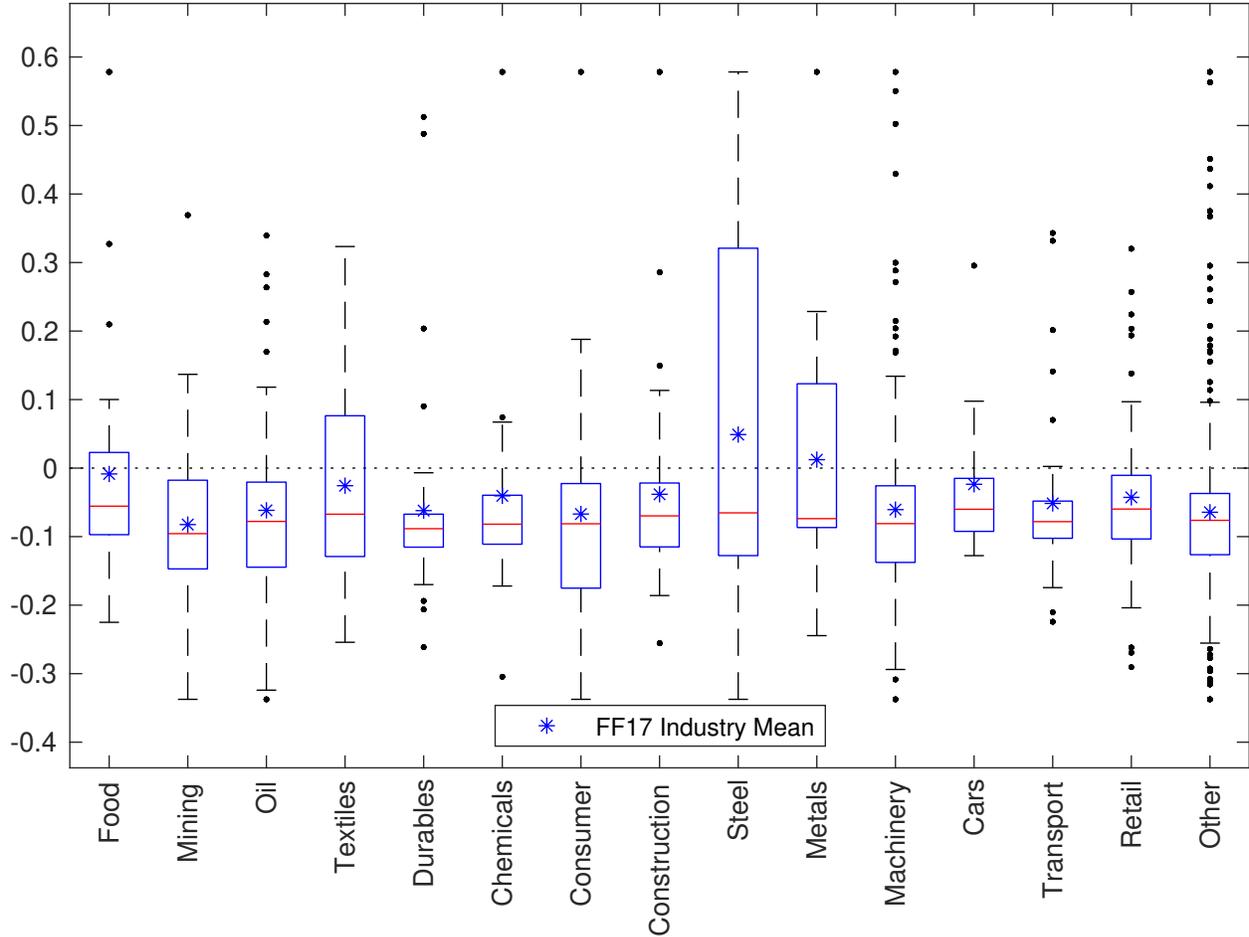
Figure 5: Estimates of the correlation between permanent and short-term cash flow shocks. This figure presents the box plots of the maximum likelihood estimates of the correlation coefficient, ρ, in the cash flow model of equations (1)–(3) for all firms within each of the 17 industries defined by Fama and French (1997). The sample data covers 10,136 firms, from 1971 to 2018.

Table 1: Definitions and descriptive statistics of variables

This table presents the definitions and the descriptive statistics of the variables used in the analysis. The descriptive statistics are: Number of observations (N); mean; standard deviation, and the percentiles p5, p25, p50, p75, and p95. The sample covers the period 1971 to 2018.

Panel A: Variable definition

| Variable name	Variable definition
Operating cash flow	EBITDA (oibdp) minus change in working capital, defined as in Table 1 of Chang et al. (2014).
Cash flow-to-assets	Ratio of *Operating cash flow* to lagged book value of total assets (at)
Cash flow-to-initial assets	Ratio of *Operating cash flow* to the first observation of the book value of total assets (at)
Cash savings	Ratio of the change in cash holdings (che) from year $t-1$ to t to the lagged book value of total assets (at)
Gross equity issuance	Ratio of the proceeds from sales or conversions of common and preferred stock (sstk) to the lagged book value of total assets (at)
Equity issuance dummy	Dummy variable equal to one if *Gross equity issuance* is larger than 5%, and zero otherwise
Net equity issuance	Proceeds from sales or conversions of common and preferred stock (sstk) minus dividends on common stock (dvc), dividends on preferred stock (dvp), and repurchased shares (prstkc) divided by the lagged book value of total assets (at)
Net equity issuance dummy	Dummy variable equal to one if *Net equity issuance* is larger than 5%, and zero otherwise
Market-to-book ratio	Book value of total assets (at) + market cap (csho*prcc_f) − book equity (ceq) divided by total assets
ln*(Total assets)*	Logarithm of the book value of total assets (at)
Industry cash flow volatility	Mean of the standard deviation of firms' cash flow-to-assets ratio, for all firms in the same two-digit SIC industry and year

Panel B: Descriptive statistics

	N	Mean	Stdev	p5	p25	p50	p75	p95
Cash flow-to-assets	197,168	0.074	0.263	−0.300	0.034	0.113	0.184	0.334
Cash flow-to-initial assets	207,554	1.507	18.403	−0.681	0.038	0.185	0.542	4.161
Cash savings	197,597	0.025	0.196	−0.156	−0.024	0.000	0.032	0.241
Change in cash-to-assets	197,549	0.000	0.093	−0.145	−0.026	0.000	0.025	0.144
Gross equity issuance	191,165	0.080	0.308	0.000	0.000	0.001	0.014	0.416
Equity issuance dummy	191,165	0.151	0.358	0.000	0.000	0.000	0.000	1.000
Net equity issuance	182,611	0.045	0.281	−0.095	−0.022	−0.001	0.003	0.337
Net equity issuance dummy	182,611	0.126	0.331	0.000	0.000	0.000	0.000	1.000
Market-to-book ratio	181,410	2.180	2.662	0.762	1.085	1.444	2.210	5.637
ln*(Total assets)*	208,467	5.070	2.379	1.261	3.402	5.011	6.693	9.179
Industry cash flow volatility	201,480	0.177	0.188	0.060	0.091	0.134	0.204	0.382

Table 2: Tests of non-stationarity of operating cash flows

Table entries for ADF (columns 1 to 3) and for KPSS (columns 4 to 6) tests are the percentage of times that the ADF test is *not* rejected and the KPSS test *is* rejected for three different confidence levels, 10%, 5%, 1%, respectively. The null hypothesis of the ADF test is that firm's cash flows have a unit root, i.e., they are non-stationary. The null hypothesis of the KPSS test is that the firm's cash flows are stationary. There are 10,136 firms in our cash flow panel. For any given firm there is a maximum 48 yearly observations of cash flows between 1971 to 2018. The ADF and KPSS tests are run for each firm's cash flow time series when the number of available observations exceeds a given minimum (reported in Minimum observations). The last column reports the total number of firms tested for each required minimum number of observations. Critical values for the ADF and KPSS tests are not tabulated for firms with fewer than 15 cash flow observations.

ADF			KPSS			Minimum	Number
10%	5%	1%	10%	5%	1%	observations	of firms
87.1	91.4	97.1	91.4	88.2	82.8	48	373
83.8	90.0	96.3	89.0	84.5	76.6	38	792
82.8	89.5	96.2	85.1	79.3	68.9	30	1,616
85.1	91.1	97.0	70.2	61.7	47.6	15	6,342

Table 3: Decomposition of standard deviation by industries or estimation groups

This table shows the decomposition of the total standard deviation of several firm-specific outcome, financing policy, product market and innovation variables into the between- and within-group standard deviations. Firms are grouped according to their 4-digit SIC code (SIC4), their 17-industry classifications in Fama and French (1997) (FF17), or allocated into groups of ten firms sorted by their average annual cash flow growth rate within each three-digit SIC code ('Groups'). The data is for all yearly observations of the 10,136 Compustat firms with at least (not necessarily consecutive) 10 years of cash flow data between 1971 and 2018.

| | Standard deviation | | | | | |
| | Within- | | | Between- | | |
	SIC4	FF17	Groups	SIC4	FF17	Groups
1. Technology variables						
Capital-to-labor ratio	1.06	1.29	1.04	0.92	0.99	1.25
Operating leverage	0.76	0.89	0.75	0.57	0.40	0.61
2. Outcome variables						
Annual sales-to-assets	1.54	1.63	1.54	0.61	0.45	0.68
Annual earnings-to-assets	0.34	0.35	0.34	0.07	0.06	0.13
Annual sales growth	0.47	0.47	0.46	0.07	0.05	0.08
3. Policy variables						
Cash holdings	0.16	0.18	0.16	0.06	0.05	0.09
Cash savings	0.19	0.20	0.19	0.02	0.02	0.03
Equity issuance	0.28	0.28	0.27	0.07	0.05	0.08
Credit lines	0.40	0.42	0.39	0.17	0.06	0.20
CAPEX-to-assets	0.07	0.07	0.07	0.03	0.03	0.04
Total debt-to-assets	0.27	0.28	0.26	0.09	0.03	0.09
4. Product market and innovation variables						
De Loecker et al. (2018) markups	0.38	0.44	0.39	0.13	0.12	0.25
R&D expense-to-assets	0.83	0.91	0.82	0.32	0.21	0.45
Number of patents	0.91	0.96	0.87	0.44	0.28	0.45
Kogan et al. (2017) market value of patents	1.22	1.28	1.17	0.51	0.33	0.55

Table 4: Summary of the parameter estimates of the cash flow model

This table summarises the maximum likelihood estimates of the cash flow model parameters, $\hat{\mu}, \hat{\sigma}_P, \hat{\sigma}_A, \hat{\rho}$,

$$P_t = (1 + \mu)\, P_{t-1} + \sigma_P\, P_{t-1}\, \varepsilon_t^P$$
$$A_{i,t} = P_t + \sigma_A\, P_{t-1}\, \varepsilon_{i,t}^A$$

where $\varepsilon_{i,t}^A = \rho \varepsilon_t^P + \sqrt{1 - \rho^2} \varepsilon_{i,t}^T$, the correlation $\rho \in (-1, 1)$, P_t is the unobserved asset productivity, and $A_{i,t}$ are firm i cash flows in year t, for $i = 1, \ldots, N$ and $N = 10$. The permanent shock ε_t^P and transitory shock $\varepsilon_{i,t}^T$ are uncorrelated and distributed as $\mathcal{N}(0, 1)$. The model parameters are estimated for each of the 918 three-digit SIC-cash flow growth groups of firms. The descriptive statistics are: number of model parameter estimates (#est.); mean; (Total) standard deviation, decomposed into between- (sd_b), and within-three-digit SIC industry (sd_w) variation; and the percentiles p5, p25, p50, p75, and p95. The sample covers the period 1971 to 2018.

Panel A: Parameter estimates

| | | | Standard deviation | | | | | | | |
	#est.	Mean	Total	sd_b	sd_w	p5	p25	p50	p75	p95
$\hat{\rho}$	918	-0.055	0.143	0.107	0.121	-0.232	-0.122	-0.076	-0.023	0.229
$\hat{\sigma}_P$	918	0.826	0.584	0.377	0.432	0.145	0.301	0.651	1.264	1.901
$\hat{\sigma}_A$	918	0.755	1.411	0.905	1.225	0.029	0.060	0.093	0.357	4.486
$\hat{\mu}$	918	0.148	0.104	0.069	0.081	0.021	0.064	0.119	0.218	0.345

Panel B: Values of t-statistics of the parameter estimates

| | | | | Proportion of | | | | | | |
| | | | Standard | p values | | | | | | |
	#est.	Mean	deviation	< 0.05	< 0.01	p5	p25	p50	p75	p95
$\hat{\rho}$	918	-27.383	98.947	0.558	0.503	-94.612	-9.383	-1.058	-0.201	2.122
$\hat{\sigma}_P$	918	37.595	59.465	0.842	0.757	1.635	2.612	5.425	42.477	181.635
$\hat{\sigma}_A$	918	9.217	36.124	0.758	0.622	1.001	2.003	3.319	5.791	19.838
$\hat{\mu}$	918	7.921	51.590	0.464	0.386	-3.415	0.808	1.368	3.937	31.186

Panel C: Correlations between the parameter estimates

	$\hat{\rho}$	$\hat{\sigma}_P$	$\hat{\sigma}_A$	$\hat{\mu}$
$\hat{\rho}$	1.000			
$\hat{\sigma}_P$	-0.196***	1.000		
$\hat{\sigma}_A$	-0.243***	0.445***	1.000	
$\hat{\mu}$	0.038	0.471***	0.176***	1.000

Table 5: Estimates of the correlation between permanent and short-term cash flow shocks by industry

This table summarises the distribution of the maximum likelihood estimates of the correlation between permanent and short-term cash flow shocks, $\hat{\rho}$. This parameter is estimated, together with the other cash flow model parameters, for each of the 918 three-digit SIC-cash flow growth groups of firms, using firm-specific cash flow data from 1971 to 2018. The summaries show the number of firms, and the mean, standard deviations and percentiles p5, p25, p50, p75, and p95 of $\hat{\rho}$ for all firms in each industry of the 17-industry classification in Fama and French (1997).

Fama-French Industry	Number of firms	Mean	Standard deviation	p5	p25	p50	p75	p95
Food	418	−0.01	0.18	−0.19	−0.10	−0.06	0.02	0.58
Mining and Minerals	494	−0.08	0.12	−0.27	−0.15	−0.10	−0.02	0.09
Oil and Petroleum Products	723	−0.06	0.13	−0.23	−0.14	−0.08	−0.02	0.21
Textiles, Apparel and Footware	282	−0.03	0.14	−0.20	−0.13	−0.07	0.08	0.24
Consumer Durables	373	−0.06	0.14	−0.21	−0.12	−0.09	−0.07	0.20
Chemicals	209	−0.04	0.18	−0.17	−0.11	−0.08	−0.04	0.58
Drugs, Soap, Parfumes and Tobacco	330	−0.07	0.16	−0.23	−0.18	−0.08	−0.02	0.17
Construction and Construction Materials	516	−0.04	0.15	−0.17	−0.12	−0.07	−0.02	0.29
Steel Works	192	0.05	0.26	−0.34	−0.13	−0.07	0.32	0.58
Fabricated Products	125	0.01	0.22	−0.24	−0.09	−0.07	0.12	0.58
Machinery and Business Equipment	1,431	−0.06	0.16	−0.26	−0.14	−0.08	−0.03	0.27
Automobiles	179	−0.02	0.10	−0.13	−0.09	−0.06	−0.01	0.30
Transportation	488	−0.05	0.11	−0.17	−0.10	−0.08	−0.05	0.20
Retail Stores	761	−0.04	0.11	−0.20	−0.10	−0.06	−0.01	0.20
Other	3,615	−0.06	0.13	−0.23	−0.13	−0.08	−0.04	0.16

Table 6: Cash flow risk parameters: Within-industry comparisons

This table shows the within-industry Spearman's rank correlation between each of the firm characteristics listed below and the estimates of the operating earnings' risk parameters: the volatilities of permanent shcoks (σ_P), short-term shocks (σ_A), and their correlation, $\hat{\rho}$. The within-industry rank correlations are the result of sorting all firms within each industry by each parameter and each characteristic. Industries are defined using several classifications: three- and four-digit SIC codes, and the 17-industry classification in Fama and French (1997) (FF17). The risk parameters are estimated, together with the other cash flow model parameters, for each of the 918 three-digit SIC–cash flow growth groups of firms, using firm-specific cash flow data from 1971 to 2018.

	$\hat{\rho}$			$\hat{\sigma}_A$			$\hat{\sigma}_P$		
	SIC3	SIC4	FF17	SIC3	SIC4	FF17	SIC3	SIC4	FF17
1. Risk choices									
Capital-to-labor ratio	0.74	0.68	0.65	−0.07	−0.08	0.17	−0.13	−0.14	0.09
Operating leverage	0.73	0.66	0.63	−0.25	−0.25	−0.59	−0.17	−0.18	−0.49
Total debt-to-assets	0.76	0.70	0.67	−0.36	−0.33	−0.61	−0.47	−0.45	−0.65
Acquisitions-to-assets	0.13	0.11	−0.23	−0.08	−0.07	0.10	−0.16	−0.16	0.04
2. Risk outcomes									
Equity volatility	−0.16	−0.12	−0.43	0.56	0.52	0.61	0.71	0.68	0.63
Asset volatility	−0.14	−0.10	−0.45	0.62	0.58	0.66	0.77	0.76	0.70
Distance to default	0.74	0.67	0.66	−0.07	−0.15	0.00	−0.27	−0.33	−0.15
Term loans maturity	−0.02	0.00	0.22	−0.30	−0.27	−0.24	−0.42	−0.40	−0.20
Term loans spread	−0.02	−0.05	−0.23	0.22	0.26	−0.05	0.26	0.30	0.04

Table 7: Savings sensitivity of cash flow and cash flow shocks

This table presents estimates of the sensitivity of cash savings to cash flow, which are obtained from the slope coefficient of the regression of the yearly change in the stock of cash divided by total assets (*Cash savings*) on the firm's *Cash flow-to-assets*. Control variables include the lagged logarithm of *Total assets* and *Market-to-book ratio*. The sample period from 1971 to 2018. The data is sorted and classified into subsamples according to the ratio $\hat{\sigma}_P/\hat{\sigma}_A$, and $\hat{\rho}$, which are the ratio of the estimated volatilities of and correlations between permanent and short-term cash flow shocks, respectively, common to all firms in the same SIC3–cash flow growth group. The coefficients are estimated using the fourth-order linear cumulants estimator (LC4) following Erickson et al. (2014), and standard errors (in parentheses) are computed using the optimal GMM weighting matrix. Estimates followed by the symbols ***, **, or * are statistically significant at the 1%, 5%, or 10% levels, respectively. The number of observations for each subsample is in square brackets. Please refer to Table 1 for the definition of all the variables.

	Subsamples by values of $\frac{\hat{\sigma}_P}{\hat{\sigma}_A}$:		
Subsamples by $\hat{\rho}$:	Above 50%	Above 60%	Above 70%
$\hat{\rho}_i \leq -0.03$	-0.169***	-0.193***	-0.194***
	(0.022)	(0.025)	(0.028)
	[55,734]	[44,480]	[31,723]
$\hat{\rho}_i \geq 0.03$	0.122***	0.114***	0.123***
	(0.035)	(0.036)	(0.038)
	[20,842]	[15,713]	[13,079]

	Subsamples by values of $\frac{\hat{\sigma}_P}{\hat{\sigma}_A}$:		
Subsamples by $\hat{\rho}$:	Above 50%	Above 60%	Above 70%
$\hat{\rho}_i \leq -0.02$	-0.172***	-0.196***	-0.199***
	(0.022)	(0.025)	(0.028)
	[57,377]	[46,123]	[33,366]
$\hat{\rho}_i \geq 0.02$	0.105***	0.098***	0.104***
	(0.029)	(0.031)	(0.033)
	[21,758]	[16,629]	[13,546]

Table 8: Cash flow risk and equity issuance

This table presents estimates from regressions of equity issuance variables on the parameters of cash flow risk. The dependent variable is *Gross equity issuance* in columns 1 and 2, *Equity issuance dummy* in columns 3 and 4, *Net equity issuance* in columns 5 and 6, and *Net equity issuance dummy* in columns 7 and 8. The sample period is from 1971 to 2018. The sample includes all firm-years in which a firm experiences a positive change in the cash-to-asset ratio. $\hat{\sigma}_P$, $\hat{\sigma}_A$, and $\hat{\rho}$ are the group-specific estimates of volatilities and the correlation between permanent and short-term cash flow shocks. All specifications include year fixed effects. Specifications 2, 4, 6, and 8 also include two-digit SIC industry fixed effects. All variables are defined in Table 1. The numbers in square brackets are economic effects, computed as the average change in the dependent variable for a one standard deviation change in the regressor, divided by the sample mean of the dependent variable. Standard errors (in parentheses) are bootstrapped and clustered at the three-digit SIC industry level. Estimates followed by ***, **, or * are statistically significant at the 1%, 5%, or 10% levels, respectively.

	Gross Equity		Gross Equity Dummy		Net Equity		Net Equity Dummy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hedging need ($\hat{\rho}$)	−0.036***	−0.029***	−0.036**	−0.030**	−0.030***	−0.023**	−0.037**	−0.031**
	(0.010)	(0.010)	(0.017)	(0.015)	(0.010)	(0.009)	(0.015)	(0.012)
	[−0.062***]	[−0.051***]	[−0.032**]	[−0.027**]	[−0.089***]	[−0.070**]	[−0.040**]	[−0.034**]
Permanent shock vol ($\hat{\sigma}_P$)	0.020***	0.014***	0.056***	0.036***	0.024***	0.017***	0.053***	0.035***
	(0.008)	(0.005)	(0.011)	(0.006)	(0.007)	(0.004)	(0.010)	(0.005)
	[0.137***]	[0.100***]	[0.202***]	[0.130***]	[0.283***]	[0.201***]	[0.228***]	[0.149***]
Short-term shock vol ($\hat{\sigma}_A$)	0.003	0.003	0.007***	0.006***	0.004*	0.004**	0.007***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.057]	[0.046]	[0.061***]	[0.047***]	[0.106*]	[0.102**]	[0.067***]	[0.054***]
Industry cash flow vol	0.042	0.011	0.065*	0.017	0.031	0.009	0.054*	0.013
	(0.029)	(0.022)	(0.035)	(0.026)	(0.027)	(0.023)	(0.030)	(0.023)
ln(*Total assets*)	−0.010***	−0.011***	−0.014***	−0.016***	−0.011***	−0.013***	−0.015***	−0.017***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Cash flow-to-assets	−0.388***	−0.375***	−0.250***	−0.236***	−0.376***	−0.362***	−0.251***	−0.235***
	(0.049)	(0.046)	(0.033)	(0.031)	(0.044)	(0.043)	(0.031)	(0.029)
Market-to-book	0.039***	0.038***	0.027***	0.025***	0.031***	0.031***	0.024***	0.023***
ratio residuals	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y	N	Y
Observations	76,795	76,795	76,795	76,795	73,167	73,167	73,167	73,167
Adjusted R^2	0.32	0.33	0.15	0.18	0.30	0.31	0.15	0.18

Table 9: Estimates of the cash flow model parameters under different cash flow definitions

This table summarizes the maximum likelihood estimates of the cash flow model parameters, $\hat{\mu}, \hat{\sigma}_P, \hat{\sigma}_A$,and $\hat{\rho}$ for different definitions of the firm's cash flow from operations. Panel A reproduces the main estimates in Table 4, where operating cash flow is defined as EBITDA minus the change in working capital. Panels B and C are for EBITDA and EBITDA net of depreciation, respectively. The model parameters are estimated for each of the 918 three-digit SIC-cash flow growth groups of firms. The sample covers the period 1971 to 2018.

Panel A: Cash flow from operations =
EBITDA − Δ Working Capital

	Mean	Median	Standard deviation
$\hat{\rho}$	−0.055	−0.076	0.143
$\hat{\sigma}_P$	0.826	0.651	0.584
$\hat{\sigma}_A$	0.755	0.093	1.411
$\hat{\mu}$	0.148	0.119	0.148

Panel B: Cash flow from operations =
EBITDA

	Mean	Median	Standard deviation
$\hat{\rho}$	−0.052	−0.065	0.121
$\hat{\sigma}_P$	0.609	0.438	0.461
$\hat{\sigma}_A$	0.412	0.097	0.711
$\hat{\mu}$	0.117	0.097	0.081

Panel C: Cash flow from operations =
EBITDA − Depreciation

	Mean	Median	Standard deviation
$\hat{\rho}$	−0.059	−0.069	0.136
$\hat{\sigma}_P$	0.981	0.916	0.624
$\hat{\sigma}_A$	0.993	0.150	1.516
$\hat{\mu}$	0.154	0.144	0.128

Table 10: Model-implied asset volatilities

This table presents a comparison of the distributions of empirical and model-implied asset volatilities. The volatilities are estimated for each of the 918 three-digit SIC-cash flow growth groups of firms. Model-implied asset volatilities are calculated using the model of Décamps et al. (2017) (see Appendix C) and the estimated cash flow parameters reported in Table 4. The remaining parameters are $r = 0.08$, $\lambda = 0.02$, $p = 1.06$, $\Phi = 0.002$, $\eta^P = \eta^T = 0.4$, and $\xi^T = \xi^P = 0.4$. Model-implied asset volatilities are winsorized at p5 and p95. The descriptive statistics are: Number of observations (N); mean; standard deviation, and the percentiles p5, p25, p50, p75, and p95.

	N	Mean	Stdev	p5	p25	p50	p75	p95
Empirical asset volatility	703	0.476	0.155	0.270	0.358	0.447	0.584	0.740
Model-implied asset volatility								
Baseline parameters	703	0.559	0.317	0.166	0.307	0.495	0.716	1.340
Baseline and $r = 0.05$	555	0.588	0.386	0.143	0.296	0.490	0.761	1.570
Baseline and $\Phi = 0.005$	701	0.538	0.304	0.161	0.301	0.477	0.679	1.288
Baseline and $\xi^T = \xi^P = 0.6$	845	0.491	0.241	0.177	0.295	0.448	0.626	1.041

Internet Appendix

Table A.1: Tests of non-stationarity of firms' cash flows subject to other screens

ADF and KPSS tests for the non-stationarity of firms' cash flows. See Table 2 for the definition of table entries. Columns 1 to 6 report the percentage of firms with cash flows subject to permanent shocks. Panel A includes cash flows of firms with annual asset growth less than 200% in any given year. Panel B includes firm-year cash flow observations when assets value is above 10 million.

Panel A: Firms with asset growth < 200%

ADF			KPSS			Minimum	Number
10%	5%	1%	10%	5%	1%	observations	of firms
85.1	92.1	97.0	92.1	88.4	82.5	46	303
83.2	90.3	96.7	89.3	85.7	77.9	38	642
82.9	90.5	97.0	85.4	80.6	70.7	30	1,152
84.9	91.3	97.3	70.4	62.1	47.9	15	4,678

Panel B: Firm-year observations when assets > 10 million

ADF			KPSS			Minimum	Number
10%	5%	1%	10%	5%	1%	observations	of firms
87.2	93.8	97.8	92.8	89.7	82.9	46	321
85.1	92.1	97.3	89.9	86.7	78.5	38	656
84.3	91.6	97.3	86.0	81.6	71.9	30	1,189
86.5	92.3	97.5	72.1	64.0	50.1	15	5,256

Table A.2: Estimates of the cash flow model parameters using cash flow subject to other screens

Summary statistics of parameter estimates using cash flows subject to other screens. See Table 4 for the definition of table entries. Panel A includes cash flows of firms with annual asset growth less than 200% in any given year. Panel B includes firm-year cash flow observations when assets value is above 10 million.

Panel A: Firms with asset growth < 200%

	Mean	Median	Standard deviation
$\hat{\rho}$	-0.042	-0.076	0.149
$\hat{\sigma}_P$	0.693	0.505	0.520
$\hat{\sigma}_A$	0.246	0.077	0.421
$\hat{\mu}$	0.145	0.115	0.117

Panel B: Firm-year observations when assets > 10 million

	Mean	Median	Standard deviation
$\hat{\rho}$	-0.042	-0.073	0.151
$\hat{\sigma}_P$	0.720	0.502	0.557
$\hat{\sigma}_A$	0.349	0.078	0.617
$\hat{\mu}$	0.147	0.120	0.130